A METHODOLOGY FOR THE OPTIMIZATION OF DISAGGREGATED SPACE SYSTEM CONCEPTUAL DESIGNS

DISSERTATION

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AFIT-ENV-DS-15-J-062

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DISSERTATION

Presented to the Faculty

Department of Systems Engineering and Management

Graduate School of Engineering and Management

Air Force Institute of Technology

Air University

Air Education and Training Command

In Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

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June 2015

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AFIT-ENV-DS-15-J-062

Abstract

Optimal design techniques have proven to be an effective systems engineering tool. Using systems architecture as the foundation, this research explores the use of mixed variable optimization models for synthesizing and evaluating disaggregated space system concepts. Model-based conceptual design techniques are used to identify and assess system architectures based upon estimated system cost, performance trades, and cost risk. The Disaggregated Integral System Concept Optimization (DISCO) methodology is introduced, and then applied to representative space-based missions. Several results are obtained that indicate significant cost effectiveness gains from the optimization of multi-orbit and multi-function/multi-orbit disaggregated space systems. Savings of \$82 million are identified for an optimized fire detection system. Savings of \$5.7 billion are identified for an optimized defense weather system. This optimized defense weather system was also shown to have a reduction in cost risk due to failures of \$117 million. The general methodology has broad applicability for model-based conceptual design (MBCD) of many system types, but is particularly useful for dynamic disaggregated space systems.

Acknowledgments

I would like to express my sincere appreciation to my faculty advisor, Dr. John Colombi, for his guidance and support throughout the course of this research effort. His insight, experience, and guidance were instrumental. I would also like to thank my wife and daughters for their loving support throughout the many long days and nights. Additionally I would like to thank Donald Boucher and other members of the Remote Sensing System Directorate at the Space and Missiles Systems Center for the support provided in this endeavor.

<div align="right">Robert E. Thompson</div>

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A METHODOLOGY FOR THE OPTIMIZATION OF DISAGGREGATED SPACE SYSTEM CONCEPTUAL DESIGNS

I. Introduction

Space system architectures based upon large, complex, aggregated satellites are costly, lack resilience, and are susceptible to catastrophic failure risks. Disaggregated space system architectures are a proposed solution to reduce space system costs, increase resiliency, and reduce the risk posture of critical defense related space systems. Further analysis is necessary to determine whether these potential benefits are obtainable. Current methods of space system conceptual architecting are largely based upon the design, assessment, and improvement of a few candidate architectures. These current methods are inadequate to effectively design, assess, and optimize the vast conceptual design space associated with these types of systems. A research methodology is desired that improves upon the state of the art in computer automated design, assessment, and optimization of complex disaggregated space system architectures. The developed methodology is termed Disaggregated Integral System Component Optimization (DISCO). This methodology is applied to a basic space-based fire detection problem, and then a realistic spaced-based weather mission. Significant contributions are made in space system modeling, optimization, and analysis methods. The application results also hold significant promise as conceptual designs capable of addressing critical needs in a cost effective and low risk manner.

Problem

The general problem is space systems designed using traditional methods are experiencing exponential cost and complexity growth while budgets for developing and

producing these space systems are increasingly more constrained. An example of how incremental improvements in functionality have caused exponential increases in satellite mass and program life cycle cost is shown in Figure 1. This exponential space vehicle mass and program life cycle cost growth will lead to significant affordability and resilience problem for the U.S. Department of Defense (DOD). Optimization of disaggregated space systems is a potential solution to this growing problem, however, new methods are required to design disaggregated space systems.
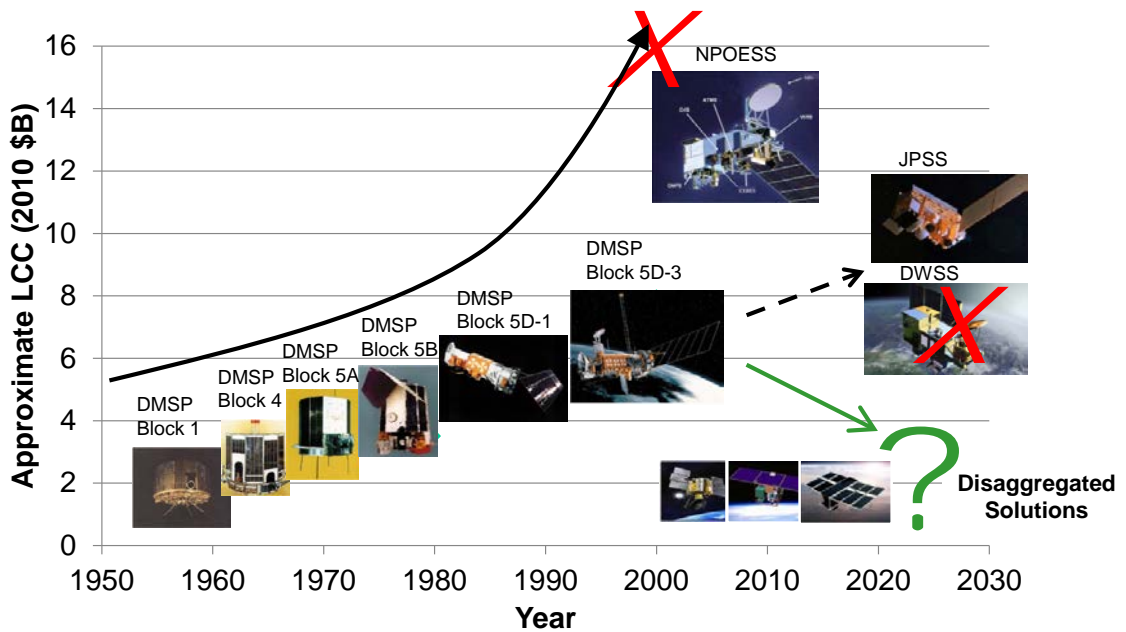
Figure 1. Exponential Space System Life Cycle Cost (LCC) Growth Example

Research Objectives

The overall objective of the proposed research is the development of an effective methodology capable of automated generation, evaluation, and optimization of novel disaggregated space system architectures. There are four corollary sub-objectives to meet

this overall objective. The first sub-objective is to develop methods capable of quantifying the impact of the disaggregation strategy. The second sub-objective is to develop methods capable of optimizing concept designs for various disaggregation approaches (multi-orbit, multi-function). The third sub-objective is to develop methods that are capable of effectively identifying and analyzing the significant trades associated with lifecycle costs and system performance for disaggregated space system conceptual architectures. The fourth sub-objective is to develop methods capable of assessing the impacts of stochastic variables on disaggregated space system architectures. A verified automated capability to design, assess, and optimize disaggregated space-system architectures in a quantifiable manner that addresses significant trades, competing disaggregation strategies, and impacts of stochastic variables would represent a significant advancement in the general system architecting practice. It would especially make a significant impact in the space architecting and policy community that is currently struggling to find and justify strategies that would increase the resiliency and responsiveness of space systems in a budget constrained environment.

Research Questions/Hypotheses

The primary research question addressed in this dissertation is: What is an effective methodology for the conceptual design, assessment, and optimization of disaggregated space system architectures? Four corollary research questions necessary to answer this primary research question are identified as:

1. How does one model/optimize disaggregated space system concepts?

2. How does one model/optimize multi-orbit/multi-function disaggregated space system concepts?

3. How does one conduct trade studies and requirements sensitivity analysis for disaggregated space system concepts?

4. How does one assess the impact of stochastic variables on disaggregated space system architectures?

Several hypotheses were made related to this research. First, it was hypothesized that the Disaggregated Integral System Concept Optimization (DISCO) methodology could be demonstrated as an effective methodology for finding concept solutions that were as cost effective as existing concepts developed through traditional architecting methods. Second, it was hypothesized that heterogeneous (mixed) satellite constellations would be identified as near-optimal multi-orbit disaggregation solutions. Third, it was hypothesized that near-optimal solutions will consist of heterogeneous constellations when multi-function and stochastic parameters are taken into account. Finally, it was hypothesized that disaggregated space systems would have less cost risk due to failures.

Methodology Overview

The Disaggregated Integral System Concept Optimization (DISCO) methodology was developed to provide an analysis capability needed to solve complex disaggregated space system concept optimization problems. An overview of the DISCO methodology is shown in Figure 2. The methodology consists of four model components (system architecture, system dynamics, system performance, and system optimization). A

reference system architecture model is developed. This reference system architecture

forms the basis for an integrated optimization, dynamics, and performance model that is

used to identify near optimal solutions. Of note, the architecture uses Systems Modeling

Language (SysML) descriptions to document realizable and parameterized system types.

The solutions are then analyzed and used to update the system reference architecture.

The methods used to develop the reference architecture and maintain concordance

between the models are discussed in more detail in Appendix B. Further details on these

components and how they are developed are discussed in chapters II – IV.
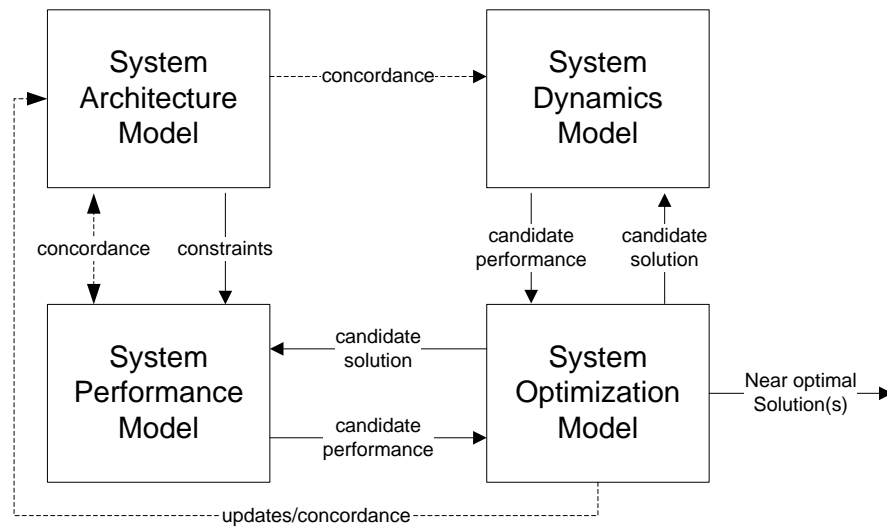
Figure 2. DISCO methodology overview

The details of the DISCO iterations are presented in Figure 3. The DISCO

process consists of a Genetic Algorithm (GA) routine that searches over many

generations to find candidate solutions. The GA is executed via multiple iterations to

increase confidence in the local optimal solutions. Stochastic parameters are then

updated via a Monte Carlo routine to determine the impact of randomized model

parameter (if applicable). Finally, a sensitivity analysis is conducted by executing

multiple cases with updated model parameters associated with system requirements.

Further details on the application of the DISCO process are discussed in Chapters II-IV.
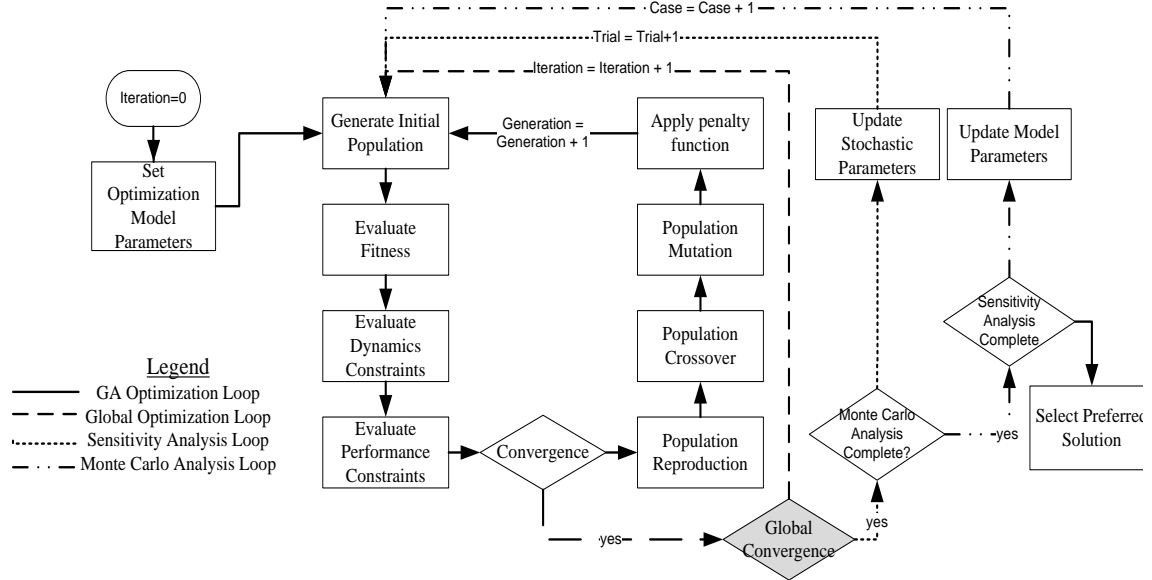
Figure 3. DISCO process

The DISCO methodology represents a significant evolution in space system

optimization methods. A literature review summarizing extant methods is provided in

Appendix A. Relevant research and significant methodology variations are also

highlighted in chapters II-IV as applicable. The DISCO methodology enables the

optimization of heterogeneous system types, system parameter optimization, optimized

system requirement trades, and stochastic analysis in an integrated methodology. The

utility of these advancements and the limitation of previous space system optimization

methodologies are discussed in Chapters II-IV.

Assumptions/Limitations

Assumptions made in this research relate to model fidelity, system scaling, and

orbital parameters. The research conducted assumes that existing cost and performance

models are sufficiently accurate for system concept design. Cost models such as the

Unmanned Space Vehicle Cost Model (USCM), the Small Satellite Cost Model (SSCM),

the NASA Instrument Cost Model (NICM), and the NASA Operations Cost Model

(NOCM) were used without modification. The accuracy of cost estimates utilized in this

research is dependent upon the fidelity of these pedigreed cost models. Cost estimates

were compared with analogous systems whenever possible to verify the applicability of

the models. The DISCO methodology assumes that system parameters are sufficiently

estimated using parametric sizing relationships. Space vehicle and payload parameters

such as mass, weight, and power are scaled using analogous components according to

parametric relationships outlined in chapter 14 and 17 of [1]. These sizing relationships

are inexact but necessary for the DISCO methodology. Scaling results were compared to

multiple analogous systems when available and margin was applied to minimize the

impact of scaling estimate inaccuracies. Orbits used in this analysis are assumed to be

circular and orbital perturbations are assumed to have a minimal impact on coverage and

revisit requirements. Circular orbits enable assessment due to predictable ground tracks

and orbital perturbations have a minimal impact over the relatively short analysis time

periods used. Consequently it is assumed that the space vehicles used will have a

capability to maintain a near circular orbit and desired constellation phasing. These

assumptions are consistent with those found in the researched literature and are likely

appropriate for early conceptual designs.

The research methods discussed are currently limited to the space systems

engineering domain and Walker satellite constellations [2]. The DISCO methodology

could be extended beyond space systems; however the current formulations are only

directly applicable to earth orbiting space system concept design problems. The DISCO methodology requires that the performance of the disaggregated system can be accurately estimated using physics-based models. An extension to manned or remotely piloted vehicles could be accomplished, but would be difficult due to the effects of operator proficiency and performance. The methods are also currently limited to Walker satellite constellations based upon the number of evenly spaced satellite planes and satellites per plane. These limitations do not appreciably reduce the significance of the research as the methodology is still applicable to many real world conceptual design problems.

Implications

A vision for disaggregated space systems was presented in [**3**] identifying disaggregation as a promising new strategy to address disruptive challenges related space systems. The research summarized in this dissertation has significant implications related to the validation and eventual achievement of this vision. Achievement of this vision has far reaching impacts related to the reduction of space system life cycle costs, increased space system resiliency, reduced development and production timelines, improved space systems engineering education and knowledge base, a stabilized industrial base, and an improved competitive environment.

This research has the potential to significantly reduce space system life cycle costs. The DISCO methodology is broadly applicable to numerous space system applications including weather, global precision navigation and timing, imagery, communications, missile warning, missile defense, and space situational awareness. Cost effectiveness gains identified through the DISCO methodology have the potential to

dramatically reduce the cost of developing and producing the systems associated with these mission areas.   The combined cost of these space systems represents a significant fraction of the DoD budget. Consequently, cost effectiveness gains in these space systems have the potential to enable the acquisition community to close budget gaps in a fiscally constrained environment.

This research has the potential to significantly improve space system resiliency. Space system architectures consisting of a few highly capable space vehicles are vulnerable to catastrophic failures and are relatively easy targets. Space system architectures consisting of a multitude of distributed small satellites reduce these vulnerabilities and significantly change the targeting calculus. Optimizing space system designs to minimize risk weighted cost enables system architects to trade system capability and system risk.

This research has the potential to significantly reduce space system development and production timelines. Large aggregated satellite development, production, and deployment timelines are highly dependent upon parallel timelines. If delays occur in the development or production of a single component or payload then the entire timeline is impacted. Disaggregated space system architectures reduce these critical path linkages and enable the deployment of capabilities in a shortened timeline.

This research has the potential to improve space systems engineering education and increase the space systems knowledge of body. Current space systems engineering courses reinforce systems engineering methods that identify a small number of feasible alternatives. Significant effort is spent manually developing alternative concepts, conducting subsystem trades, and calculating results for each potential solution. The

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methods identified by this research enable the automated generation, assessment, and optimization of vast numbers of conceptual design. This automated process thus enables students to focus their efforts on system level trades and more detailed design aspects. Concepts with smaller less complex satellites also increase opportunities for students to get hands-on development experience with flight hardware. This hands-on experience developing space systems increases student learning as demonstrated by the multitude of university cubesat programs.

Disaggregated space system research has the potential to stabilize the space system industrial base and improve the competitive environment. Disaggregated space systems have the potential to "stabilize lower-tier suppliers through stable production and launch" [**3**]. Space system concepts based upon large aggregated satellites tend to create programs that are so large and complex that only a few industrial developers are capable of system development and production. Disaggregated systems have the potential to expand the competitive base to include a greater number of potential developers.

Preview

This dissertation is organized according to the scholarly article format. Chapters II through IV are drawn from manuscripts published or in review with predominant space systems or systems engineering journals. Chapter II, titled "Methodology Development and Introduction" addresses research question #1 identified above. This chapter is drawn from a manuscript titled *Disaggregated Space System Concept Optimization: Model Based Conceptual Design Methods* that has been accepted for publication in Systems Engineering, the journal of the International Council on Systems Engineering. Chapter II

introduces the DISCO methodology and demonstrates utility by optimizing a notional fire detection system. Chapter III, titled "Multi-function Optimization and Sensitivity Analysis Methods" addresses research question #2 and #3 identified above. This chapter is drawn from a manuscript titled *Model-Based Conceptual Design Optimization Methods: Disaggregated Weather System Follow-on* that has been accepted for publication in the American Institute of Aeronautics and Astronautics (AIAA) Journal of Spacecraft and Rockets. Chapter III expands the DISCO methodology enabling multi-function optimization using a realistic Weather System Follow-on (WSF) problem as an example application. Chapter III also demonstrates how a sensitivity analysis can be performed by changing critical system requirements (modeled as constraints) such as required average revisit time. Chapter IV, titled "Stochastic Analysis Methods" addresses research question #4. The text is drawn from a manuscript titled *Disaggregated Space System Concept Optimization: Stochastic Analysis Methods* that has been submitted to the Institute of Electrical and Electronics Engineers (IEEE) Transaction on Aerospace and Electronic Systems Journal. The manuscript is currently in review. Chapter IV finalizes the research by demonstrating impact of stochastic launch vehicle and space vehicle failure rates on life cycle cost risk for the WSF concept.

II. Methodology Development and Introduction

Introduction

Today's space systems have far reaching impacts to military, civilian, and commercial
end-users globally. They provide a multitude of mission applications such as
communications; global navigation and timing; precise weather and climate inputs;
global intelligence, surveillance, and reconnaissance; and a continuous record of our
earth's surface. However, the systems that provide these capabilities can be complex,
costly, with high technical risks [**4**]. It has been hypothesized that the "vicious circle of
space acquisition" leads to large, complex, and expensive satellites that lack resiliency.
Furthermore, it has been proposed that applying disaggregation strategies to space system
conceptual design could improve cost effectiveness and/or reduce risk exposure to
catastrophic failures. [**3**]

Current methods of space system conceptual architecting are largely based on the
design, assessment, and improvement of a few candidate architectures. These methods
are inadequate to effectively design, assess, and optimize the vast conceptual design
space associated with disaggregated space systems.

The vast trade space associated with system architectures in the concept phase can lead to
analysis difficulties. Simpson and Dagli state that when a system under design is "highly
dynamic and contains a large number of context-specific, adaptable interfaces, the task of
system architecting can become overwhelming" [**5**]. Disaggregated space systems
represent highly dynamic systems with a large number of context-specific adaptable

interfaces. Therefore, particular attention should be paid to developing methodologies that increase effectiveness of the conceptual design process if the potential benefits of disaggregated space systems are to be achieved. To this end, this paper introduces a novel Disaggregated Integral System Concept Optimization (DISCO) methodology and applies it to a space-based fire detection mission.

Background

Disaggregation Strategies

Recently, disaggregation has gained considerable interest as a system architecting approach to improve the resiliency and robustness of space systems, as well as increase affordability, technology refresh rates, and launch and space industrial base stability. Disaggregation is defined as "the dispersion of space-based missions, functions, or sensors across multiple systems spanning one or more orbital plane, platform, host, or domain" (Air Force Space Command, 2013). The potential improvements that disaggregated space systems have to offer are highly dependent upon effective conceptual design and system architecting.

It has been proposed that disaggregation can be categorized into five distinct architecting approaches consisting of multi-orbit disaggregation, functional disaggregation, hosted payloads, fractionation, and multi-domain disaggregation [**6**]. Some or all of these approaches may be appropriate for a particular conceptual architecture problem.

Multi-orbit disaggregation is the dispersion of sensors or payloads across multiple satellites spanning one or more orbital planes. Multi-orbit disaggregation is a familiar

concept for space systems engineers. Multi-orbit disaggregation is often employed to meet geographic coverage or revisit requirements. Satellite constellations such as the Global Positioning System (GPS), Galileo, IRIDIUM, and the Defense Meteorological Satellite Program (DMSP) employ payloads on multiple satellites in separate orbital planes at the same orbital altitude to meet coverage requirements. Weather satellites also routinely disperse sensors providing similar functionality in low earth orbit and geosynchronous orbit to provide global coverage and meet varied coverage and revisit rate requirements. The U.S Air Force Space Command (AFSPC) is currently investigating the potential of replacing or augmenting the baseline GPS constellation with numerous small NavSats [7].

Multi-function disaggregation is the dispersion of functions from large multi-function satellites to smaller functionally cohesive spacecraft. A recent example of multi-function disaggregation is the Space Environment NanoSatellite Experiment (SENSE) program. Two SENSE satellites launched in November 2013 successfully demonstrated the dispersion of space weather functionality onto functionally cohesive cubesats [8]. The strategic and tactical protected communications mission currently provided by Advanced Extremely High Frequency (AEHF) satellites are being studied for functional disaggregation [3].

Hosted payload disaggregation disperses sensors or payloads from large satellites onto other defense, civil, or commercial satellite systems. A recent example of hosted payload disaggregation is the Commercially Hosted Infrared Payload (CHIRP) experiment. The dispersion of GPS functionality onto Positioning, Navigation, & Timing (PNT) hosted payloads to augment a revamped GPS constellation is being considered by the Air Force.

Fractionated space systems are intended to disperse the subsystem functionality of a satellite among multiple satellites.   The Defense Advanced Research Project Agency (DARPA) F6 program was an example of fractionated space system architecture [**9**]. Lastly, multi-domain disaggregation is a strategy where functions are dispersed across multiple domains such as land, sea, space, or cyber. The Air Force Space-based Space Surveillance System (SBSS) is an example of multi-domain disaggregation.

Many practical concept trade studies may include combinations of the disaggregation strategies outlined above. For example Multi-orbit/Multi-function disaggregation enables the dispersion of sensors and payloads commonly aggregated on large satellites to be sized and dispersed onto smaller functionally cohesive satellites placed in orbits conducive to the mission. The design of the Weather System Follow-on (WSF) concept can be viewed as a multi-function/multi-orbit disaggregation problem. Significant potential life-cycle savings have been identified using the DISCO methodology to assess the WSF conceptual design problem [**10**]. The proposed DISCO methodology enables the systematic analysis and comparison of these disaggregation concepts.

Model-Based Conceptual Design (MBCD)

Model-Based Systems Engineering (MBSE) is the "formalized application of modeling to support system requirements, design, analysis, verification and validation, beginning in the conceptual design phase and continuing throughout development and later life cycle phases" [**11**]. The primary output of MBSE is a coherent model of the system and emphasis is placed on evolving and refining the model using model-based methods and tools (Friedenthal et al., 2012). Model-Based Conceptual Design (MBCD)

is "the application of MBSE to the exploratory research and concept stages of the generic lifecycle" [12]. During conceptual design, it is unlikely that the system architect has high fidelity models for all associated areas. A system architect is likely limited to parametric cost models and initial functional and performance models. Therefore, the integration of standardized systems engineering tools that are capable of integrating parametric cost models with functional and performance models could provide significant utility. MBCD processes and methodologies are still maturing. The DISCO methodology is an example of applying MBCD techniques to the space system domain. In this approach, stakeholder's needs are mapped to quantitative measures of effectiveness. Then, component technologies are associated to potential system types. Stakeholder's needs are refined by providing early conceptual feedback of operational performance and affordability. Finally, feasible and potential near-optimal solutions are identified and analyzed via an integrated optimization construct.

Systems Architecture

Systems architecture is the "selection of system elements, their characteristics, and their arrangement". The arrangement and characteristics of these elements must meet requirements and implement functions in a near-optimal and technically mature and consistent manner [13]. The system architecture process includes defining the architecture, analyzing and evaluating the architecture, and documenting and maintaining the architecture [13]. Traditional system architecting is iterative and highly dependent upon engineering analysis, heuristics and experience; consequently, the synthesis of multiple system architectures can be very resource intensive.

The selection of a preferred system architecture solution is highly dependent upon metrics and evaluation criteria. Automation of the synthesis and evaluation of alternative system architectures is a primary goal of a MBCD methodology. Significant academic research has been conducted on evaluating and ranking architectures based upon expert evaluations. Multi Attribute Utility Theory is often used to rank and evaluate alternative architectures [14]. Additionally, Simpson and Dagli described the use of genetic algorithms to conduct alternative analysis/evaluation in [5]. Their effort is largely focused on subjective assessments of a system and the fuzzy modeling of quality attributes. This research effort proposes that a quantitative approach applying metaheuristic optimization techniques to integrated cost and dynamic system models would significantly improve the performance and quality of the system architecting process. Additionally this approach could potentially minimize inherent weighting towards favored or familiar technologies or designs associated with expert opinion based architecture assessment.

System Design Optimization

Significant research has been conducted in space system conceptual design optimization. This growing body of research has applied heuristic design optimization techniques (i.e. simulated annealing, genetic algorithms, or particle swarm optimization) to the conceptual design of space systems. Heuristic algorithms have been widely applied to optimize spacecraft component, spacecraft configuration, and launch vehicle configuration conceptual design problems. Additionally heuristic algorithms have been applied to Distributed Task Constellation (DTC) concepts, and Distributed Space System (DSS) concepts. These DTC and DSS concepts are analogous to some of the

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disaggregation strategies previously identified. However, an integrated MBCD methodology that is capable of simultaneously optimizing spacecraft conceptual designs and disaggregated architectures may represent a significant improvement in the conceptual design of space systems architectures.

The use of genetic algorithms to optimize the configuration of a spacecraft was introduced by Mosher in 1999. Mosher introduced the Spacecraft Concept Optimization and Utility Tool (SCOUT) which uses a genetic algorithm to identify and assess the inclusion of various component technologies on a spacecraft [**15**].   These techniques have been extended to the conceptual design of numerous spacecraft types and space related systems such as launch vehicles [**16**].

Heuristic methods for optimizing the conceptual designs of Distributed Task Constellations (DTC) were introduced by Matossian in 1996. Matossian used a simulated annealing algorithm to identify the near-optimal inclusion of legacy sensors in conceptual space-based Earth Observation System (EOS) designs according to science utility measures [**17**].   Matossian's concept of distributed task constellations is similar to the concept of multi-function disaggregation. The method introduced was limited to linear optimization techniques to select clusters of heritage sensors for configuration of notional spacecraft based upon the subjective performance of various Earth Observing System (EOS) sensors.

A methodology for optimizing distributed satellite constellations was introduced by Jilla and Miller in 2004. Their Multi-objective Multidisciplinary Design Optimization Systems Architecting (MMDOSA) methodology uses a simulated annealing algorithm with numeric orbital simulation to optimize the conceptual design of

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homogeneous spacecraft [18]. The DSS concepts assessed are analogous to multi-orbit disaggregation problems. The MMDOSA methodology is based upon modeling and assessing space systems as networks of homogeneous systems.   Consequently, the methodology was limited to the optimization of homogenous spacecraft types [19]. Selva's Rule Based System Architecting (RBSA) methodology extended the DTC optimization introduced by Matossian. RBSA included the treatment of instrument selection, assignment of instruments, and mission scheduling for a conceptual NASA EOS constellation design [20].   The RBSA approach represented a significant progression in space system conceptual design optimization for multi-function disaggregation problems. However, methodology was limited to the clustering of existing sensors on spacecraft and does not enable the optimization of sensor/payload and orbital parameters for meeting system requirements.

Based on extant literature, a methodology does not exist that applies MBCD techniques to the optimization of multi-orbit disaggregation problems, where heterogeneous or mixed satellite types are possible. Also, a methodology has not documented the optimization of multifunction/multi-orbit disaggregation concepts where the individual spacecraft system conceptual designs are optimized for the specific orbit rather than the clustering of existing sensors.   This paper presents the DISCO methodology and applies it to a multi-orbit disaggregation problem where heterogeneous system types are possible.

DISCO Methodology

The primary motivation for the Disaggregated Integral System Concept Optimization (DISCO) methodology is the enablement of improved system analysis and optimized solutions across all disaggregation types. An overview of all potential logical decompositions is presented in Figure 4.
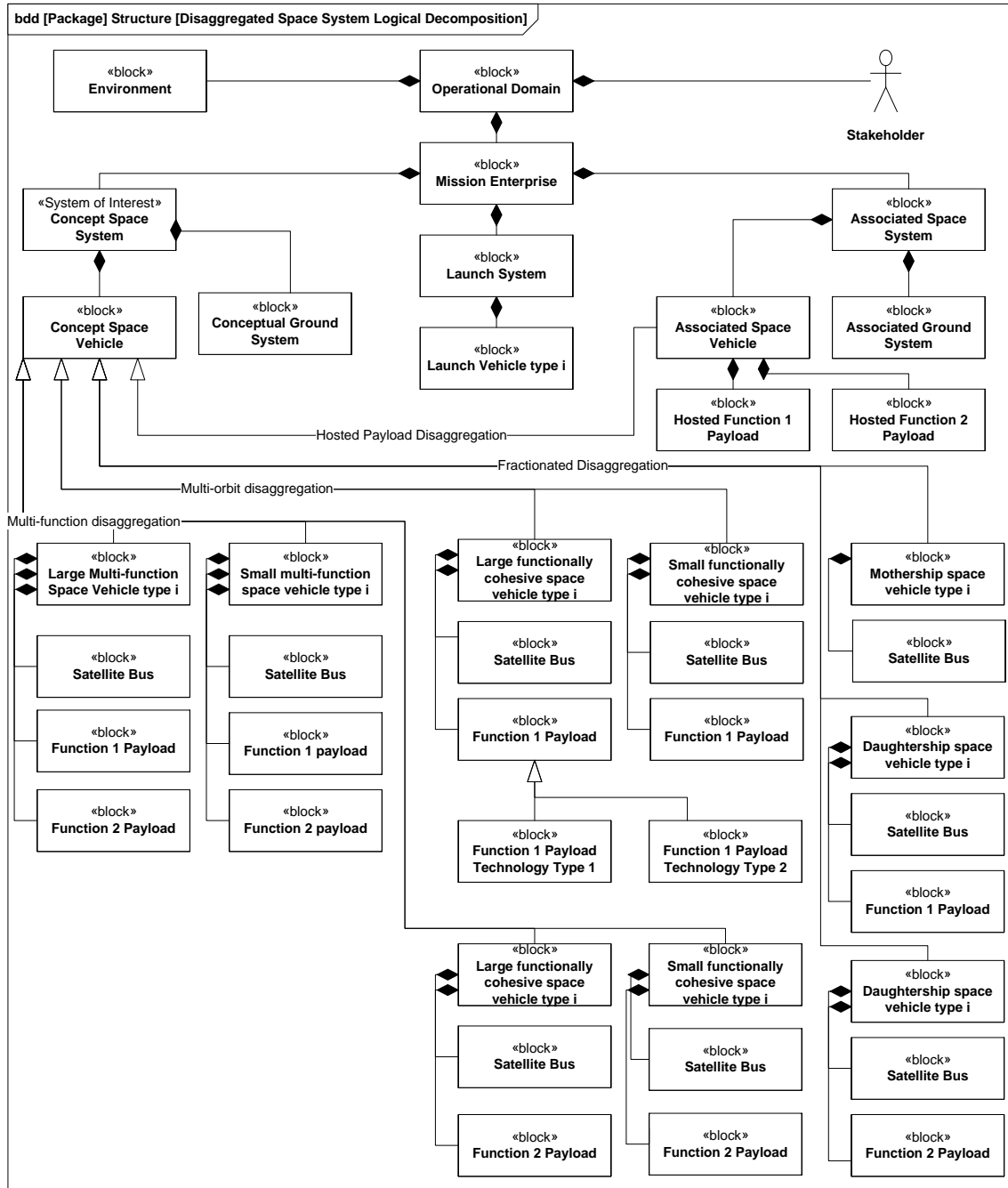
Figure 4. Disaggregated space system logical decomposition strategies summary

Figure 5 shows a general overview of the DISCO approach. The general DISCO

approach is similar to the MMDOSA approach presented by Jilla and Miller, consisting

of the following components: reference system architecture, dynamics models,

performance assessment models, and mixed variable optimization functionality.

The architecture reference model forms the basis of the disaggregated space system optimization approach. The primary stakeholder needs, mission objectives, system requirements, and logical/physical architecture artifacts are modeled in an MBSE architecture tool. The architecture reference model is kept in concordance with performance/quality assessment and dynamics simulations via engineering analysis. This concordance may be maintained via an automated electronic means or through manual manipulation as currently implemented. Requirements documented in the architecture reference model (e.g. maximum revisit rate) form the constraints of the performance assessment.
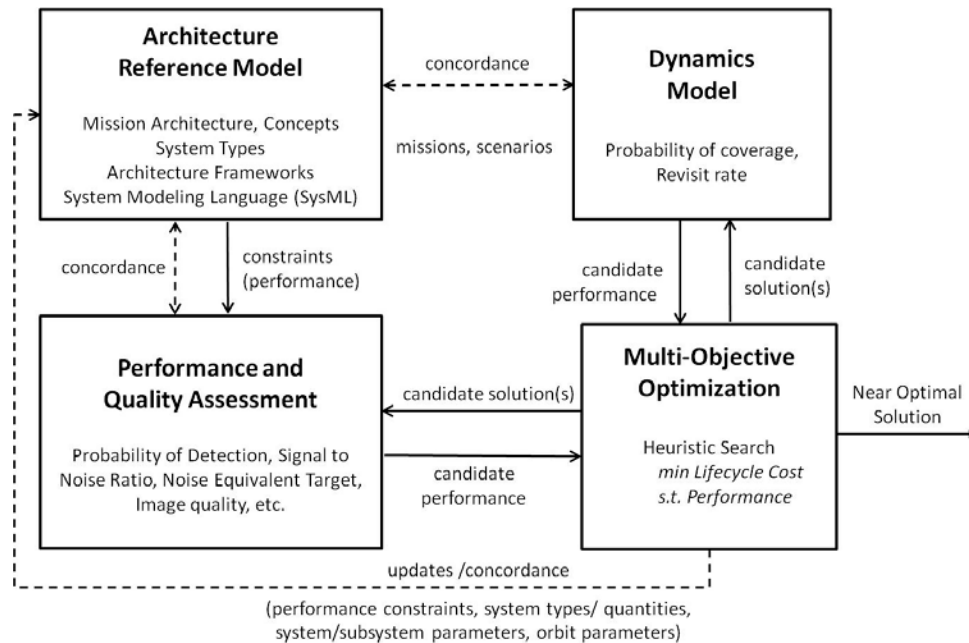
Figure 5. DISCO methodology MBCD approach

The performance assessment models consist of performance estimating equations, sizing equations, and cost estimating equations that are used to calculate the estimated

performance and cost of candidate architectures. Candidate solutions (represented as individuals in the genetic algorithm) are evaluated and the estimated performance and cost of the solution are returned to the optimization routine. The dynamics model consists of a numeric simulation capability or analytic coverage estimating equations used to assess the dynamic performance of the conceptual system. The dynamics model inputs candidate solutions (individuals) and returns dynamics related performance measures. The optimization routine evaluates the fitness of each of the candidate solutions as well as the feasibility (e.g. constraint violations) of each of the candidate solutions. The optimization routine then outputs the best feasible candidate architecture for further evaluation.

The methodology assumes that the performance of disaggregated space architectures is dependent upon the type of systems, the number of systems, the performance of each system, and the orbital dynamics of the constellation. The optimization component outputs candidate near-optimal disaggregated space system architectures in the form of a design variables that represent the number of systems included in the architecture, the critical design variables (i.e. payload aperture diameter) and the constellation orbital parameters. These near-optimal solutions are assessed and evaluated. The candidate solutions and corresponding calculated functions (i.e. satellite mass, volume, and power) are used to update the reference architecture.

The DISCO methodology employs three process steps:

       1. Develop reference architecture

       2. Develop optimization/assessment models

       3. Evaluate solutions and update the architecture.

The example problem presented in the subsequent application section of this paper is structured to follow these DISCO process steps.

Develop Reference Architecture

Reference architectures can be viewed as a template for system solutions based upon a generalized set of solutions. According to the INCOSE SE handbook it is critical that a reference architecture be created in the early stages of the conceptual design of a system to "whatever depth is necessary to identify technological risks, assess technology readiness, and generate early cost and schedule projections" for a program [**13**]. The DISCO methodology adopts four steps from the Object Oriented Systems Engineering Method (OOSEM) "specify and design system process" in order to develop a reference architecture [**21**]. Accordingly, the four tasks used to develop reference architectures are:

1. Analyze stakeholder needs

2. Analyze system requirements

3. Define logical architecture

4. Synthesize candidate physical architectures

Analyze Stakeholder Needs

Stakeholder needs can be analyzed and established via numerous methods including stakeholder elicitation and causal analyses comparing existing capabilities and desired capabilities. Accurately assessing needed mission functions and their corresponding measures of effectiveness is critical to the effective application of DISCO. The DISCO optimization model is currently structured to assess operational cost effectiveness as the primary Measures of Effectiveness (MOE) by minimizing estimated life cycle cost (LCC) subject to performance requirements. However it should be

possible to structure the optimization objective function as a value function. Future

research is planned to assess alternative optimization model formulations to maximize the

weighted value model subject to varying performance constraints. Analysis of

stakeholder needs concludes with the documentation of mission needs, mission

objectives, mission requirements, measures of effectiveness, enterprise use cases, and an

operations concept documented in the reference architecture. These items should be

documented in an MBSE software tool in the corresponding requirements diagrams, use

case diagrams, and block definition diagrams.

Analyze System Requirements

System requirements for DISCO applications are analyzed via traditional MBSE

means such as mission scenario/system context assessment and identification of critical

system properties and constraints. The output of this analysis is the documentation of

system requirements in requirements diagrams contained in the reference architecture

model. Accurate identification of space system performance requirements is critical for

the analysis of disaggregated space systems. These requirements often fall into the

general categories of coverage, refresh rates (such as revisit), mission data delivery and

dissemination timeliness, mission data geolocation, and mission data accuracy/sensitivity

requirements. The DISCO methodology varies from other distributed space system

optimization methods, such as MMDOSA, by incorporating space system performance

requirements as constraints in the design optimization model. DISCO models these

system requirements as constraints that can be varied to perform requirements trade

studies. This requirements traceability often requires the modeling of estimated payload

or sensor performance. Consequently, physics based models are necessary to determine

the estimated payload/sensor performance. This analysis sometimes requires subsystem and component modeling that is traditionally abstracted during system architecture studies.

Define Logical Architecture

Defining the logical architecture is a critical step in the DISCO methodology. During this process task the system is decomposed into logical components and the interconnections needed to satisfy system requirements are described (Friedenthal, Moore and Steiner 2011). The logical decomposition forms the framework for the disaggregated space system optimization. The varying disaggregation strategies summarized in Figure 4 represent the various logical decomposition strategies.

Synthesize Candidate Physical Architectures

The transition from a logical architecture to a candidate physical architecture is a critical step for the DISCO methodology. The reference logical architecture is decomposed into logical and physical nodes. The distribution of functions to specific payloads/sensors and orbital compartments represent the transition from a logical node architecture to a physical node architecture. Ultimately, the DISCO optimization routine produces size, weight, and power, and performance estimates for the spacecraft and the mission payload. These estimates are used to update the physical architecture block definition diagrams with initial specification values. These specification values can then be used as technical performance measures to assess development status in the system development life cycle stage.

Develop assessment/optimization models

Cost Assessment Models

Life-cycle costs for space systems are traditionally calculated using cost estimating relationships derived from historical programs. Several relevant parametric cost models have been previously developed including the Unmanned Satellite Cost Model (USCM), the Small Satellite Cost Model (SSCM) and the NASA Instrument Cost Model (NICM). The DISCO methodology enables the identification of system types within these corresponding cost model parameters.

Performance Assessment Models

Performance assessment models for disaggregated space systems are scenario and technology dependent. The needed performance models are linked to the space system performance requirements determined in the analyze system requirements task of developing an architecture model.   The performance models output expected performance values for candidate architecture. These performance values are then evaluated as part of the constraint equations.

Dynamics Assessment Models

Assessment of spacecraft dynamics is integral to the evaluation of disaggregated space systems. Space systems are commonly evaluated for dynamics related requirements such as coverage and revisit rates. The dynamics of individual systems vary in a disaggregated space system context. Consequently dynamics models must be developed that are capable of determining whether space vehicles are capable of meeting these requirements. Coverage models are commonly based upon analytic models and numerical simulations. Analytic models can estimate area access rates and consequently

can be used to estimate percent coverage for a specific time or revisit rates. Numeric simulations are required to accurately calculate revisit rates and coverage figures of merit. This is especially true for discontinuous or regional based coverage areas and distributed systems where coverage overlaps exist. The DISCO methodology enables analytic dynamic assessment as well as numeric simulation assessment.

Optimization Models

The DISCO methodology is intended to analyze architectural problems where performance and cost are dependent upon the number and type of dynamic systems in the architecture, as well as the performance of individual sensors or payloads. The optimization of a disaggregated space system is dependent upon an integrated constellation design (evaluated via a dynamics model) and the conceptual spacecraft design (evaluated via the performance models). The integration of these two components is structured via a mathematical optimization model. For example, the probability of detection of a space-based remote sensing system is dependent upon the number, orbit, and conceptual type of satellites in the architecture. Design problems with mixed integer problem formulations fall into the category of problems known as Mixed Variable Optimum Design Problems (MV-OPT) [22].

The general mathematical model of a MV-OPT design problem is:

Minimize

$$f(\boldsymbol{x})$$

subject to:

$$h_i(\boldsymbol{x}) = 0, i = 1..p,$$
$$g_j(\boldsymbol{x}) \leq 0, j = 1..m$$
$$x_i \epsilon D_i, D_i = (d_{i1}, d_{i2}, ..., d_{iq_i)}, i = 1..n_d$$

$$x_{iL} \le x_i \le x_{iU}, i = (n_d + 1)..(n_d + n_c)$$

where,

        $f(\boldsymbol{x})$ is the optimization objective function,

        $\boldsymbol{x}$ is the vector of design variables (x_i)

        h, represents the p equality constraint functions,

        g represents the m inequality constraint functions,

        x_{iL} and x_{iU} are the lower and upper bounds for one of the n_c continuous variables,

        n_d is the number of discrete design variables,

        D_i is the set of discrete values for the ith variable,

        q_i is the number of allowable discrete values; and

        d_{ik} is the kth possible discrete value for the ith variable.

The current formulation for a general DISCO problem is an extension of this MV-OPT formulation. The DISCO extension of the general mathematical optimization model represent a Mixed Integer Non-Linear Programming (MINLP) formulation where the objective function is the estimated system life-cycle cost which is dependent upon the integer formulation of the system type configuration and non-linear constraint equations.

The corresponding DISCO mathematical optimization formulation is[1]:

Minimize

$$f(\boldsymbol{x}) = \sum_{i=1}^{n} c_i^{\boldsymbol{dev}} x_i^{\text{dev}} + c_i^{\boldsymbol{prod}} x_i^{\text{prod}} + c_i^{\boldsymbol{ops}} x_i^{\boldsymbol{ops}} + c_i^{\boldsymbol{supt}} x_i^{\text{supt}} + c_i^{ret} x_i^{ret}$$

subject to

$$h_i = 0, i = 1..p,$$
$$g_j \le 0, j = 1..m$$
$$x_i \epsilon D_i, D_i = (d_{i1}, d_{i2}, ..., d_{iq_i}), i = 1..n_d$$
$$x_{iL} \le x_i \le x_{iU}, i = (n_d + 1)..(n_d + n_c)$$
$$x_i^{\text{dev}} = \left\{ \begin{matrix} 1 \text{ if } x_i^{\text{prod}} > 0 \\ \text{else } 0 \end{matrix} \right\}$$

where

---

[1] Note that the optimization objective function is a non-linear and discrete function despite initial appearances. The estimated system cost terms ($c_i^{dev}, c_i^{prod}, c_i^{ops}, c_i^{supt}, c_i^{ret}$) are functions of the problem design variable vector ($\boldsymbol{x}$) for satellite system types. Additionally, the system number terms ($x_i^{dev}, x_i^{prod}, x_i^{ops}, x_i^{supt}, x_i^{ret}$) are also functions of the problem design variable vector ($\boldsymbol{x}$) and can only have integer values.

$f(x)$ represents the estimated system Life Cycle Cost (LCC) (objective function)

c_i^{dev} represents the estimated development cost for system type i

x_i^{dev} represents the number of development systems of type i

c_i^{prod} represents the estimated production cost for system type i

x_i^{prod} represents the number of production systems of type i

c_i^{ops} represents the estimated operations cost for system type i

x_i^{ops} represents the number of systems of type i that require operations

c_i^{supt} represents the estimated support cost for system type i

x_i^{supt} represents the number of systems of type i that require support/sustainment

c_i^{ret} represents the estimated retirement cost for system type i

x_i^{ret} represents the number of systems of type i that require retirement/disposition

n represents the number of system types

The optimization objective function described above is a summation function of cost terms (c_i), and terms associated with the number of systems of type i (x_i). The cost coefficients are categorized based upon the life-cycle phases (i.e. development, production, operations, support, and retirement). The life-cycle phases used in this formulation are organized according to the life-cycle stages outlined in the INCOSE handbook [**13**]. For example, the cost term $\left(c_i^{dev}\right)$ represents the estimated system development cost for system type i. Therefore, the summed product $\sum_{i=1}^{n} c_i^{dev} x_i^{dev}$ represents the total estimated development costs for all systems in the architecture. The cost term c_i^{prod} represents the estimated production cost associated with system type i. Therefore the summed product $\sum_{i=1}^{n} c_i^{prod} x_i^{prod}$ represents the total estimated system production costs. The costs for operations, support (i.e. sustainment and satellite replacement costs) and retirement are calculated similarly as applicable. The term x_i^{dev} is calculated from the value of x_i^{prod}; if x_i^{prod} is greater than zero, x_i^{dev} equals one, else x_i^{dev} equals zero. The minimized objective function then represents the minimum

disaggregated system estimated life-cycle costs for the analyzed life-cycle components subject to physical and performance constraints.

The DISCO methodology has been applied using a genetic algorithm. There are multiple reasons for the choice of a genetic algorithm. First, space systems constellation design problems have "practical limits on coverage analysis with objective functions that are not differentiable, so non gradient-based optimization methods are necessary" [23]. Secondly, stochastic optimization techniques such as simulated annealing and genetic algorithms have been widely used for space system optimization problems, and continue to show significant promise. Finally, a genetic algorithm was chosen due to availability in analysis tools that are easily integrated within the MBSE framework. Industry standard genetic algorithm software routines are available that allow non-linear constraint functions, mixed-variable (i.e. discrete and continuous) design variables, and multi-objective optimization. These capabilities are necessary for the DISCO methodology based upon the MVOPT formulation.

Evaluate solutions and update architecture

The output of the DISCO optimization routine is a design vector (x) and the corresponding estimated parameters that represent a candidate physical architecture solution. The results should be assessed for accuracy, global optimality, and if possible, sensitivity to requirements and stochastic parameters. After results are sufficiently evaluated, the reference architecture (particularly the physical block definition diagram) can be updated with the estimated parameters.

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Evaluate solutions

A summary of the general DISCO optimization and results evaluation routine is summarized in Figure 6. The internal loop is representative of a standard genetic algorithm where an initial population is iteratively generated, evaluated, reproduced, crossed-over, mutated, assigned a penalty value, and assessed for convergence criteria. The results from each individual trial should be verified for physical and design limitations to ensure that the overall model is coded correctly. An external loop is then used to perform multiple optimization trials as a common global optimization technique. Confidence in the candidate solution is gained by adopting the best solution from multiple GA trials, this method is similar to a multi-start global optimization technique [22].

The outermost loop can then be used to conduct requirements trade studies. A requirement (such as max revisit time) can be varied from threshold to objective values. The corresponding sensitivity analysis results can then be used to determine the Pareto front of estimated LCC vs. varied requirements values. Additionally, the outermost loop can be used to determine the impact of stochastic parameters. The stochastic parameter can be varied according to an assumed probability distribution. Monte Carlo methods can then be used to determine the impact of the random variables on the performance of the system. A similar technique using a Monte Carlo method was discussed by Aliakbargolkar and Crawley for the conceptual architecting of resource extraction systems [24]. Once the candidate solutions have been evaluated sufficiently then the corresponding best solution can be used to update the reference architecture as a reference physical architecture design.
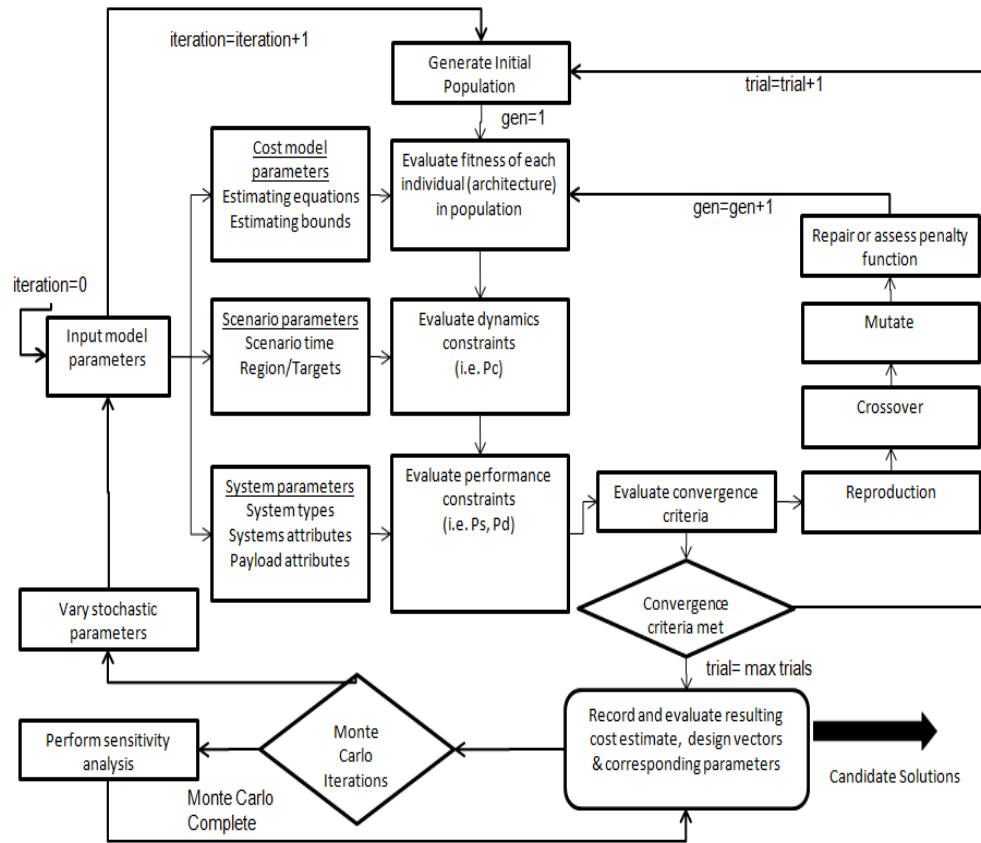
Figure 6.   DISCO optimization/results evaluation routine

Updating the Architecture

Finally, the conceptual reference architecture is updated based upon the chosen candidate solution from the optimization and evaluation technique.   Feasible solutions represent conceptual architectures that meet performance requirements. The number and types of systems in the chosen candidate solution are identified in the block definition diagrams of the reference architecture as enumerations. Calculated parameters associated with the chosen solution (i.e. preliminary size, weight, and power estimates) are added to the block diagrams and parametric diagrams where applicable. These conceptual

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estimated parameters can then serve as candidate technical performance measures for subsequent preliminary and detailed engineering design phases.

Fire detection problem

A notional early warning space-based fire detection system is presented to demonstrate the utility of the DISCO methodology to generate and assess optimized conceptual designs. Using the requirements as performance constraints, we examine designs on a cost versus performance basis to address this urgent need.

OFUEGO Reference Architecture

The development of the reference architecture is based upon the process steps outlined in develop reference architecture section of this paper, and applied to the Fire Urgency Estimator in Geosynchronous Orbit (FUEGO) problem described in [**25**] and [**26**]. The solution from DISCO will be referred to as the Optimized FUEGO (OFUEGO).

Analyze Stakeholder Needs

Stakeholder needs are first assessed by characterizing the as-is system and enterprise. Every year, billions of dollars are spent on fire suppression globally with an annual U.S. fire suppression budget of approximately one billion dollars [**25**]. Additional monetary and humanitarian damages are caused by out of control fires that are not suppressed in a timely fashion due to a lack of early detection and notification capability. Current fire detection methods rely on outdated fire spotters in towers, or multi-purpose space-based environmental sensors. Space-based fire detection data is derived from multi-purpose environmental earth observation payloads such as MODIS (Moderate

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Resolution Infrared Spectrometer) on the Aqua and Terra satellites, part of the EOS. Additionally, the imaging payloads on the Geostationary Operational Environmental Satellites (GOES) are capable of detecting large fires. These systems do not provide the sensitivity and revisit rate necessary to identify small fires early when they can be most easily suppressed.

The general operations concept for a space-based fire detection and monitoring system is shown in Figure 7. A satellite detects a heat signature associated with a developing fire. It processes and geo-locates the heat signatures and sends a warning of the potential forest fire location and intensity to an operations center. A satellite continues to provide tracking updates of the fire. Operators disseminate the fire alert information to a dispatch service, where firefighters can then respond.
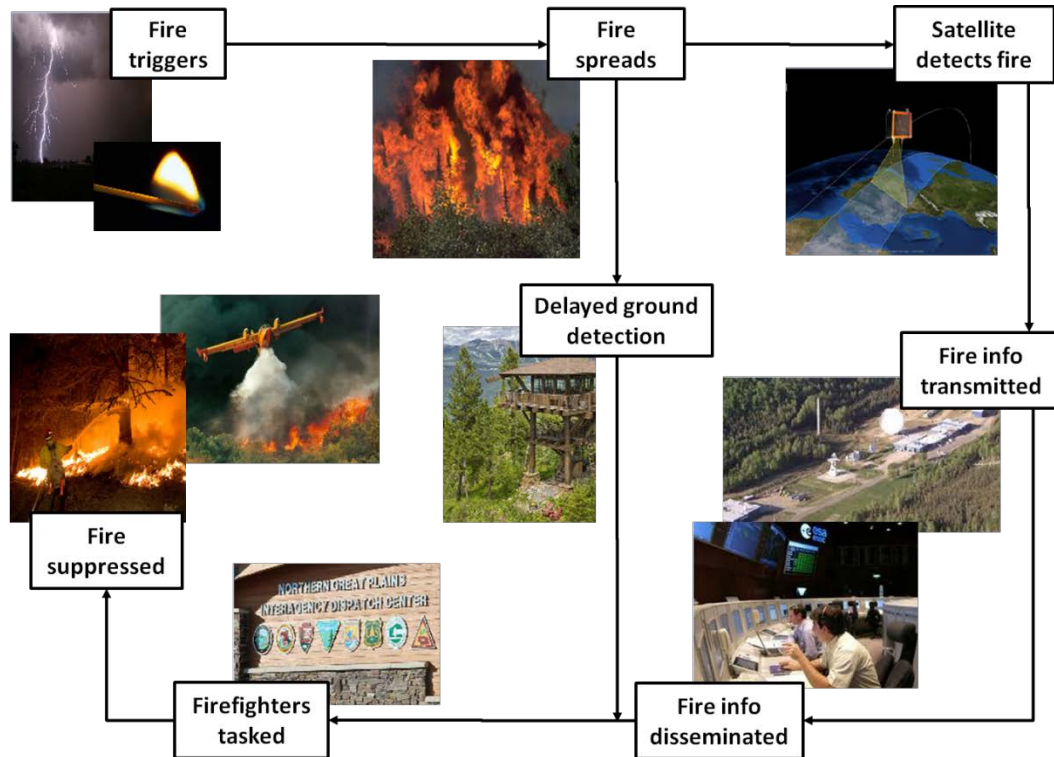
Figure 7**.** FUEGO Operational Concept, derived from [**27**].

Analyze System Requirements

OFUEGO system requirements were determined by analyzing and consolidating performance requirements summarized in [**26**] and [**25**]. These consolidated performance requirements are summarized and compared to the approximate performance of existing systems in Table 1.

Table 1. OFUEGO space system requirements summary			
	Current Capability (GOES)	**Current Capability (EOS)**	**Requirements (OFUEGO)**
Target Characteristics	Large fires	Large fires	Developing fires
Coverage Area	North / South America	Global	Critical regions 37-46° N/S
Min Detectable Fire	~3,000m^2 1100K fire	~200m^2 1100K fire	50m^2 1100K fire (SNR=90)
Probability of Detection, Pd	unspecified	unspecified	$P_d > 95\%$ within 25 min
Revisit Interval	Avg~15 min Max ~15 min	Avg ~4.4 hrs Max ~8.7 hrs	Avg <15 min Max <25 min
Mapping Accuracy	~8 km	~500 m	< 500 m
Fire Detection Timeliness	~1 hr, based on fire growth	~12 hrs	< 30 min

The reference architecture for the proposed OFUEGO mission consists of satellites, a ground system, launch vehicles, operators, users and the interfaces between these systems and actors. The initial analysis focuses on the space segment and launch vehicle selection as the primary drivers for the overall life cycle costs. The potential system types for a disaggregated OFUEGO solution were modeled in the reference architecture and are summarized in Figure 8. The legacy capability represented by on-orbit MODIS sensors could be added to the optimization problem as available systems; however, they are currently excluded to simplify the example.

Develop FUEGO Assessment/ Optimization Models

Cost assessment model

Two space system cost models are used for this application of the DISCO methodology. The first cost model is the Unmanned Space System Cost Model (USCM). This cost model was developed by the U.S. Air Force and is primarily intended to estimate the cost of large operational satellites. Specifically, the USCM 8 variant of the cost model is used for this application.

bdd [Package] Structure [OFUEGO Logical Node Architecture]

«block»
Mission Enterprise

«System of Interest»
OFUEGO System

«block»
Earth Observation System (EOS)

«block»
OFUEGO Ground System (system type 4)

«block»
EOS ground system

«block»
OFUEGO Space System

«block»
Launch System

«block»
EOS AM-1 satelite (Terra)

«block»
Large fire detection satellite (system type 1)

«block»
Launch Vehicle

«block»
MODIS

«block»
Large Satellite Bus

«block»
Mid-wave IR whisk-broom radiometer

«block»
Pegasus (System type 5)

«block»
EOS PM-1 satellite (Aqua)

«block»
Small fire detection satellite (system type 2)

«block»
Minotaur IV (System type 6)

«block»
MODIS

«block»
Small Satellite Bus

«block»
Falcon 9 (System type 7)

«block»
Mid-wave IR push-broom radiometer

«block»
Atlas 5 (System type 8)

«block»
Small fire detection satellite (system type 3)

«block»
Delta IVH (System type 9)

«block»
Small Satellite Bus

«block»
Mid-wave IR whisk-broom radiometer

Figure 8. OFUEGO Logical Node Architecture Summary

The second cost model used for the OFUEGO example is the Small Satellite Cost Model

(SSCM) developed by the Aerospace Corporation. The SSCM is primarily intended to

estimate the cost of small satellites as the name implies. The cost model was based upon

data from primarily stand-alone small research and development satellites. The USCM

and SSCM models are used to calculate the cost coefficient dependent variables in the

objective function. The estimated satellite development and production costs were

estimated using the corresponding cost estimating relationships summarized in the Space

Mission Analysis and Design (SMAD) textbook [**28**]. SMAD was also used to estimate

the production costs for the launch vehicles.

Performance Assessment

The probability of fire detection is the driving system measure of effectiveness.

The system probability of detection is calculated using:

$$P_d = P_c P_s \qquad\qquad [1]$$

where
P_d is the system probability of detection,
P_s is the probability of signal detection, and
P_c is the probability of coverage.

The probability of coverage for the required 25 minute max revisit period is equivalent to

the percent coverage calculation for the same time period. A 100% probability of

coverage for a given 25 minute time period is also equivalent to a max revisit of less than

25 minutes. Percent coverage is calculated numerically by dividing the number of points

in a given region covered in a period of time by the total number of points in a region.

The probability of signal detection is significantly more complicated to calculate

numerically because it is dependent upon the detection algorithm, sensor characteristics,

and environmental factors such as the presence and optical thickness of smoke. The

SMAD text assumes an SNR value of 88 is acceptable for a low fire detection false alarm

rate based upon heritage (MODIS) sensor performance [**28**]. A similar SNR value of 100

was identified as sufficient for fire detection in [**25**]. Likewise we assume a SNR of

greater than 100 was sufficient for fire detection. The equation for calculating SNR was:

$$SNR = \frac{Signal}{Noise} = \frac{Signal_{fire}}{\sqrt{noise_{fire}^2 + noise_{bg}^2 + noise_{det}^2}}$$

[2]

where
Signal$_{fire}$ is the number of electrons received at the detector for a 1100K fire that radiates
from a 50 m^2 area on earth,
$noise_{bg}$ (background) is the number of electrons received at the detector for the projected
surface area of one pixel,
$noise_{det}$ (detector) is the number of noise electrons per pixel for the assumed focal plane,

The *Signal*$_{fire}$ is estimated using Planck's equation at 1100K and the signal of the

background is estimated using Planck's equation at 300K (the approximate temperature

of earth's surface at noon). This calculation method is discussed in more detail in [**29**].

Dynamics Assessment Model

Systems Tool Kit (STK) software was used as the dynamics model for this

application. Spacecraft objects are created according to the corresponding design

variables and calculated sensor parameters (i.e. horizontal and vertical half angles). The

probability of coverage is calculated using the STK coverage figure of merit. The

scenario is modeled for the fire detection timeliness requirement of 25 minutes. A

physical constellation is modeled based upon the current design variables. A coverage

figure of merit is modeled based upon the corresponding coverage area requirement. The

coverage area is divided into 1 degree increments. The total probability of coverage is

then calculated by dividing the number of points covered in the required timeframe by the

total number of points.

Optimization Model

The OFUEGO optimization formulation was developed according to the DISCO

methodology for the identified system types and design variables, summarized as[2]:

Minimize

$$f(x) = c_1^{dev}x_1^{\text{dev}} + c_2^{dev}x_2^{\text{dev}} + c_3^{dev}x_3^{\text{dev}} + c_1^{prod}x_1^{\text{prod}} + c_2^{prod}x_2^{\text{prod}} +$$

$$c_3^{prod}x_3^{\text{prod}} + c_4^{prod}x_4^{\text{prod}} + c_5^{prod}x_5^{\text{prod}} + c_6^{prod}x_6^{\text{prod}} + c_7^{prod}x_7^{prod} + c^{ops} + \qquad \text{[3]}$$

$$c^{supt} + c^{ret}$$

subject to

$$h_1(x) \rightarrow N_{sp} - N_{lv} = 0$$
$$g_1(x) \rightarrow M_s - LC \leq 0$$
$$g_2(x) \rightarrow -P_d + 0.95 \leq 0$$
$$g_{i,1}(x) \rightarrow -SNR + 100 \leq 0, for\ i = 1..3$$
$$g_{i,2}(x) \rightarrow -MA + 500 \leq 0\ for\ i = 1..3$$
$$g_{i,3}(x) \rightarrow -GSD_{diff} + GSD \leq 0\ for\ i = 1..3$$
$$x_{i,0} = \begin{Bmatrix} 0\ \text{if}\ x_i = 0 \\ \text{else}\ 1 \end{Bmatrix}; i = 1..9$$
$$x_i \epsilon D_i, D_i = (1 \dots 200), i = 1..3$$
$$x_i = 1, i = 4$$
$$x_i \epsilon D_i, D_i = (1 \dots 20), i = 5..9$$
$$x_i = x_{i,1} * x_{i,2}; i = 1..3$$
$$0 \leq x_{i,3} \leq p - 1; i = 1..3$$

---

[2] Note that the optimization objective function is a non-linear and discrete function despite initial appearances. The estimated system cost terms $(c_i^{dev}, c_i^{prod}, c_i^{ops}, c_i^{supt}, c_i^{ret})$ are functions of the problem design variable vector (x) for satellite system types. Additionally, the system number terms $(x_i^{dev}, x_i^{prod}, x_i^{ops}, x_i^{supt}, x_i^{ret})$ are also functions of the problem design variable vector (x) and can only have integer values. The $x_{i,s}$ terms identified in the optimization formulation are system specific design variables included in the design variable vector (x).

$$0 \leq x_{i,4} \leq 360; i = 1..3$$
$$200 \leq x_{i,5} \leq 35,786; i = 1..3$$
$$0 \leq x_{i,6} \leq 0; i = 1..3$$
$$0 \leq x_{i,7} \leq 99; i = 1..3$$
$$0 \leq x_{i,8} \leq 360; i = 1..3$$
$$0 \leq x_{i,9} \leq 360; i = 1..3$$
$$0 \leq x_{i,10} \leq 360; i = 1..3$$
$$0.2 \leq x_{i,11} \leq 1; i = 1$$
$$0 \leq x_{i,11} \leq 360; i = 2,3$$

where

$f(x)$ is the estimated OFUEGO LCC

$h_1(x)$ is the minimum launch vehicle (LV) constraint

N_{sp} is the total number of satellite planes

N_{lv} is the total number of launch vehicles

$g_1(x)$ is the minimum LV lift capacity constraint

M_s is the total mass of satellites (kg)

LC is the total LV lift capacity (kg)

$g_2(x)$ is the minimum probability of detection constraint

P_d is the OFUEGO constellation probability of detection

$g_{i,1}(x)$ is the fire detection minimum SNR constraint

SNR is the estimated signal to noise ratio

$g_{i,2}(x)$ is the maximum mapping accuracy constraint

MA is the estimated sensor mapping accuracy (m)

$g_{i,3}(x)$ is the optical diffraction limit constraint

GSD is the G (m)

$x_{i,1}$ is the number of satellite planes (p)

$x_{i,2}$ is the number of satellites per plane (s)

$x_{i,3}$ is the walker constellation RAAN spacing (f)

$x_{i,4}$ is the walker constellation RAAN spread (Ω^*)

$x_{i,5}$ is the seed satellite orbital height (h)

$x_{i,6}$ is the seed satellite orbital eccentricity (e)

$x_{i,7}$ is the seed satellite orbital inclination (i)

$x_{i,8}$ is the seed satellite RAAN (Ω)

$x_{i,8}$ is the seed satellite argument of perigee (ω)

$x_{i,10}$ is the seed satellite true anomaly (v)

$x_{i,11}$ is the sensor aperture diameter (A_d)

$x_{i,j} \in x; g_{i,j}(x) \in g(x);$

Currently, the estimated OFUEGO operations cost term (c^{ops}) and ground system

development and production costs are assumed to be fixed values independent of the

OFUEGO concept design. Consequently c^{ops} is assumed to be \$25M, c_4^{dev} is assumed to

be \$20M, and c_4^{prod} is assumed to be \$5M; The total number of satellite planes N_{sp} is

calculated by summing the number of planes (p) for all three satellite types. The total

number of launch vehicles N_{lv} is calculated by summing the number of launch vehicles

(x_i) for i=5..9 associated with the five previously identified launch vehicle types.

The fire detection sensor aperture diameter (A_d) represents the most critical design

variable in the OFUEGO optimization problem. The concept aperture diameter

establishes the estimated mass of the fire detection payload and consequently the

estimated mass and cost of a conceptual fire detection satellite. The approach used to

estimate the mass of a satellite is based upon scaling relationships with existing similar

payloads. The scaling equations used for the OFUEGO design are:

$$R = \frac{A_d}{A_o}$$
[4]

$$M_p \sim K R^3 M_o$$

[5]

where

R is the aperture diameter ratio,
A_d is the aperture diameter of the design payload,
A_o is the aperture diameter of the reference payload,
M_p is the estimated mass of the conceptual payload;
M_o is the mass of the reference payload, and
K is a constant that addresses small R values.
The constant K is assumed to be 2 if R is less than 0.5.

Sizing estimates are constrained to R values greater than 0.2 and less than 5. These sizing

relationship equations and other sizing relationships are discussed in detail in the SMAD

textbook [1]. These sizing relationships also serve as a proxy sizing relationship for

varying payload types (i.e. whiskbroom or push-broom sensors) as the relative mass for

whiskbroom scanners are larger than push-broom sensors for comparative aperture diameters. Using this simple sizing relationship it would appear that determining the minimum cost satellite constellation design would be as simple as determining the minimal payload aperture diameter and propagating the minimal number of satellites based upon that payload to meet coverage and revisit requirements. However, the complex interaction of satellite constellation design variables in a disaggregated system makes this extremely difficult task due to conflicting combinatorial trades. A summary of the conflicting combinatorial trades are summarized in Figure 9. The relative disadvantages are shown as arrows to the left and the relative advantages are shown as arrows to the right. This conflicting combinatorial trade-space is the primary reason for using a computer aided optimization algorithm.

Payload / Satellite size

decreased performance | increased cost

Satellite altitude

decreased performance | increased coverage

Number of satellites

decreased cost | increased coverage/revisit

Number of launch vehicles

decreased cost | increased lift capacity

Push-broom sensor

decreased field of view | better sensitivity

Whiskbroom sensor

reduced sensitivity | increased field of view

Figure 9. Conflicting OFUEGO combinatorial trade summary

Evaluate OFUEGO Solutions

The candidate solutions from the FUEGO optimization routine consist of estimated life-cycle costs, design variable values, and associated technical performance measures such as estimate mass and estimated payload performance measures (i.e. SNR). The reference architecture was updated according to the techniques provided in the synthesize candidate physical architectures section.

Evaluate OFUEGO Solutions

The integrated optimization and simulation routine was executed and analyzed via multiple experimental trials according to the global optimization technique discussed in the optimization models section. Ten trials were conducted with five of the ten trials resulting in a feasible constellation design with an estimated LCC between $141M - $161M. These constellation designs all consisted of 12 small whiskbroom satellites in three planes of four satellites, using three Minotaur launch vehicles.

Four other solutions consisted of constellations based upon larger numbers of small push-broom satellites with estimated LCC between $385M and $683M. These candidate solutions appeared to converge on a local minimum associated with small push-broom satellite constellations. The final candidate solution consisted of 3 large whiskbroom satellites and had an estimated LCC of $618M. The number of similar solutions in the solution set provided confidence in the architectural solution. Additionally, all of the identified local optimization solutions consisted of homogeneous satellite constellations indicating a potential preference towards homogeneous satellite constellation solutions for this problem. It was noted that none of the near optimal

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solutions contained heterogeneous or mixed system types. The best solution design vector

from the 10 trials was selected and summarized in Table 2.

Table 2. Design vector of the OFUEGO solution

Design Vector (x)	System Type 3	System Type 4
Description	Small whisk broom	Minotaur 4 Launch Vehicle
x_i(#)	12	3
p(#)	3	
s(#)	4	
f	0	
$\Omega*$(°)	360	
h(km)	1166	
e(•)	0.0	
i(•)	48	
ω(°)	130	
Ω(°)	108	
v(•)	304	
A_d(m)	0.014	

The near-optimal constellation design solution identified is a 3/4 Walker constellation of

12 small whiskbroom scanning satellites with a 0.014m diameter infrared optic system at

1166 km orbital height. A 2-dimension representation of the constellation design solution

is displayed in Figure 10. The associated probability of coverage P_c for the highlighted

region in a 25 minute period is 100%. The maximum revisit rate was calculated as 25

minutes. The average revisit for the points in the identified region was calculated at

approximately 15 minutes.
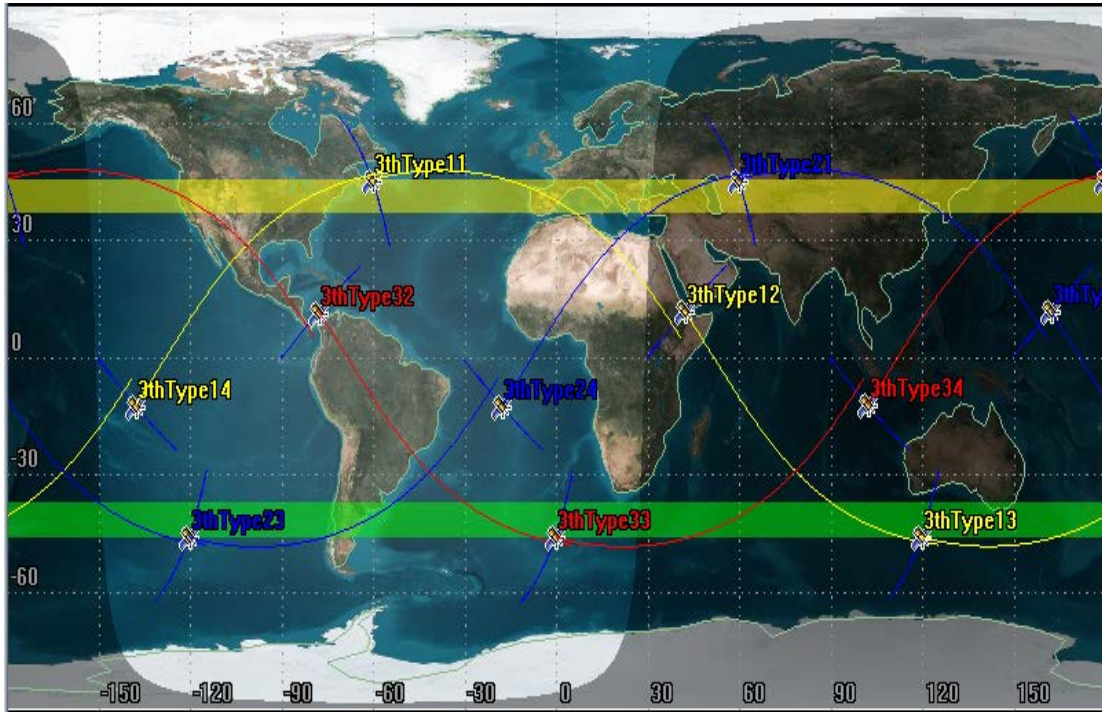
Figure 10. OFUEGO constellation design overview

bdd [Package] Design Model [OFUEGO Conceptual Design Model]

«block»
Mission Enterprise

«block»
OFUEGO System

«block»
Launch System

«block»
OFUEGO Space System

values
Number of satellite planes : Integer = 3
Number of satellites per plane (s) : Integer = 4

«block»
OFUEGO Ground System

«block»
OFUEGO Launch Vehicle

«block»
Small fire detection satellite {12}

values
Orbital inclination : degrees = 48
Estimated development cost : $K (2010) = 2300
Estimated production cost : $K (2010) = 1900
Estimated mass : kg = 28.8
Orbital height : km = 1166

«block»
Minotaur IV {3}

values
Estimated production cost : $K (2010) = 22000
Estimated lift capacity (1100km 47degs) : kg = 146

«block»
Mid-wave IR whisk-broom radiometer {12}

values
Estimated aperture diameter : m = .014
Estimated mass : kg = 8.9

«block»
Small satellite bus {12}

values
Estimated mass : kg = 19.9

Figure 11. Updated OFUEGO architecture summary

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Update OFUEGO Architecture

The resulting optimized conceptual design was used to update the reference architecture. Figure 11 displays the updated OFUEGO conceptual architecture summary. The multiplicities and the relevant estimated parameters for the system types were updated with the calculated values from the optimization routine. The system types that were not included in the OFUEGO solution were removed. The estimated properties can then be used as requirements or constraints for further detailed engineering analysis.

Results

The DISCO methodology proved capable at searching a complex design space with heterogeneous system types. Importantly, it was able to find a feasible cost-effective constellation as good as, or better than, previous fire detection constellation designs. A comparison of conceptual design results for the Optimized FUEGO (OFUEGO) and reference ESA FUEGO concepts are compared against the requirements in Table 3.

The ESA FUEGO program constellation represents a traditional system trade study. The ESA FUEGO concept design assumed the re-use of the sensors flown on the BIRD satellite. The ESA FUEGO program found that a constellation of 12 satellites in a direct Walker 3/4 constellation at 700km altitude and 47.5° inclination orbit would meet system requirements. However, the infrared sensor flown on the BIRD satellite was designed for a different mission. Specifically, it was designed to detect fires that were

4m x 4m at 1100K temperatures. It also had additional payloads for meeting secondary mission objectives.

Consequently, the FUEGO satellite concept was larger and potentially more expensive than required to detect $50m^2$ fires which were the FUEGO requirements. The ESA FUEGO program estimated that the LCC for a 7 year mission would be $203 million Euro (~ $278 million US dollars). This total system cost included 3 Rockot launch vehicles, one for each plane. Using the Small Satellite Cost Model (SSCM), the average cost of a Rockot launch vehicle, an estimated $25M for satellite operations, and an estimated $25M for ground system development the estimated LCC for FUEGO is $223M in FY 2010 dollars.

Table 3. OFUEGO results summary

	FUEGO Requirements	ESA FUEGO Reference	OFUEGO Solution
Target Characteristics	Developing fires	Developing fires	Developing fires
Coverage Area	Critical regions (37-46° N/S)	Critical regions (37-46° N/S)	Critical regions (37-46° N/S)
Min Detectable Fire	$50m^2$ 1100K fire (SNR=100)	$20m^2$ 1100K fire (SNR=100)	$50m^2$ 1100K fire (SNR=100)
Probability of Detection, P_d	$P_d > 95\%$ within 25 min	$P_d > 95\%$ within 25 min	$P_d > 95\%$ within 25 min
Revisit Interval	Avg <15 min Max <25 min	Avg =15 min Max =25 min	Avg =15 min Max =25 min
Mapping accuracy	< 500m	< 500m	< 500m
Fire Detection Timeliness	< 30 min	< 30 min	< 30 min
LCC Estimate		$223M (SSCM)	$141M (SSCM)

Interestingly, the DISCO methodology identified a very similar conceptual design to FUEGO. Both the FUEGO and OFUEGO concept designs employ a significantly smaller fire detection sensor than the design identified in the SMAD textbook. However, the MBCD methodology resulted in an optimized design with an estimated LCC that was $82 million less than the previously identified ESA FUEGO reference architecture. The

FUEGO conceptual design and the OFUEGO conceptual designs both meet the identified system requirements. However by employing a higher orbit with a smaller optical system the OFUEGO design represents a smaller less expensive satellite with coverage performance equivalent to the ESA FUEGO reference design [**26**].

Discussion

Three immediate results were assessed from the research presented in this paper. First, the DISCO methodology and MBCD framework proved applicable to the example fire detection multi-orbit disaggregation problem. Secondly, the DISCO methodology was able to effectively search a vast design space of heterogeneous system types, their quantity, continuous payload/sensor parameters and constellation orbit parameters. It was able to identify candidate near-optimal architectures that were very similar to, and more cost effective, than previously identified designs. Third, the DISCO methodology did not identify mixed or heterogeneous system types as the near optimal solution for this problem.

The presented work represents a new approach to the optimization of conceptual space system architectures, especially as related to multi-orbit heterogeneous disaggregated space systems. DISCO applies many of the principles described in Azad Madni's article [**30**] on generating novel system architectures. Such principles include: systems thinking, situational decision modeling, temporal analysis, analogical reasoning, sensitivity analysis, and option management in a computer-aided conceptual design approach.

A fire detection problem demonstrated the application of this methodology to a multi-orbit/multi-system type single function disaggregation problem. The research in this paper also demonstrated a MATLAB genetic algorithm routine with an STK orbital dynamics model.   This integrated approach was capable of evaluating thousands of iterations, tens of thousands of potential solutions and the corresponding millions of functional evaluations over the course of hundreds of hours. Similar diversity of solution space evaluations using traditional or concurrent design techniques would take months to years. Automating this process was essential.

With traditional approaches, "there is no guarantee that a system-level focus will be taken, and often the final design chosen achieves only feasibility, instead of near optimality" (Mosher 1996). Initial results indicate that the DISCO methodology may benefit the conceptual design of potential disaggregated space systems by codifying that system-level focus.

III. Multi-function Optimization and Sensitivity Analysis Methods

Introduction

Space-based earth observation satellites are critical to global weather observation and forecasting capabilities. Space-based weather satellites provide data used to help save lives and minimize damage caused by severe weather and improve weather forecasting capabilities [**31**]. Defense weather satellites provide environmental data used for planning and conducting military operations worldwide [**32**]. The Defense Meteorological Satellite Program (DMSP) satellites have been providing weather data to the defense community since the 1960's. The National Oceanic and Atmospheric Administration (NOAA) in partnership with the National Aeronautics and Space Administration (NASA) has also developed and fielded Polar Operational Environmental Satellites (POES) and Geostationary Operational Environmental Satellites (GOES) since the 1960's and 1970's respectively supporting the civil weather users. In 1995, a joint U.S. Department of Defense (DoD) and NOAA program dubbed National Polar-Orbiting Operational Environmental Satellite System (NPOESS) was established with the intent of consolidating the DMSP and POES programs. The NPOESS program was cancelled in 2010 due technical and programmatic difficulties including significant cost growth and schedule delays. In response NOAA, partnering with NASA, established the Joint Polar Satellite System (JPSS) and the Department of Defense established the Defense Weather Satellite System (DWSS). The U.S. Congress instructed the DoD to terminate the DWSS program in 2012. The DoD has since launched its next to last DMSP satellite and is

assessing options for developing the next-generation Weather System Follow-on (WSF) [**33**].

The Weather System Follow-on (WSF) program is currently planned to be developed as a disaggregated system of systems. According to US Air Force budget documents "WSF will take a disaggregated system-of-systems approach to meet specific Department of Defense needs while leveraging near-term civilian and international partnerships" [**34**]. Initial WSF architecture and technology risk-reduction studies are underway. These studies are assessing visible and infrared sensor designs, microwave radiometer designs, spacecraft bus designs, and architecture alternatives [**35**]. This paper will apply the Disaggregated Integral System Concept Optimization (DISCO) methodology to the WSF conceptual architecture problem. The applicability of the DISCO methodology to this multi-function multi-orbit disaggregation problem will be assessed. Additionally, a Disaggregated Weather System Follow-on (DWSF) conceptual design will be presented as the near optimal solution, and compared to a large multi-function satellite reference design analogous to the DWSS concept.

Five distinct disaggregation concepts have been identified in the past. These disaggregation concepts include fractionation, functional disaggregation, multi-orbit disaggregation, hosted payloads, and multi-domain disaggregation [**36**]. Fractionation is the distribution of spacecraft sub-system functionality among networked spacecraft. Functional disaggregation is the distribution of mission functions among spacecraft in the same orbital regime. Multi-orbit disaggregation is the distribution of a single mission function across different orbits. Hosted payload disaggregation distributes mission functionality onto a separate government or commercial satellite. Multi-domain

disaggregation distributes mission functionally across domains such as space, air, ground, and or cyber. The WSF problem is most naturally described as multi-function/multi-orbit disaggregation problem where functionality such as imagery and sea surface wind estimation are distributed among small functionally-cohesive spacecraft, distributed across distinct orbital planes optimized for the corresponding mission functions. In other words, the goal of the optimization routine is to place the right satellite, at the right time, in the right place to minimize life cycle costs. Hosted payload types could also be added to the WSF conceptual design space as constrained system variants but due to the lack of pedigreed cost models and the additional complexity added to the optimization formulation hosted payloads are planned to be addressed in future research.

Significant space-system optimization research has been conducted previously with regards to distributed satellites. Matossian pioneered the optimization of distributed space system architectures as compared with the optimization of space system component or parameter optimization. He applied a space system optimization method to identify near-optimal Earth Observation System (EOS) constellations by clustering existing sensors at assumed orbit height and assessing the return via subjective performance assessments [37]. Shaw et.al developed the Generalized Information Network Analysis (GINA) methodology for identifying and assessing potential distributed satellite system constellations by modeling space systems as networks [19]. The GINA methodology was intended for the identification and assessment of distributed satellite system conceptual architectures but did not address the optimization of these architectures. Jilla et al. expanded Shaw's dissertation research by integrating a space system optimization methodology with the GINA methodology. The combined identification, assessment,

and optimization methodology was termed the multi-objective, multidisciplinary design optimization systems architecting (MMDOSA) methodology [**18**]. The MMDOSA methodology was applied to the optimization of communication, radar earth observation, and terrestrial planet finding satellite constellation conceptual designs [**38**]. The MMDOSA methodology was limited to homogeneous system types and single function performance assessments. Additionally, the MMDOSA methodology did not incorporate system constraints or real-coded vs. integer parameter optimization. Selva et. al expanded Matossian's work by evaluating EOS clustering of given sensors with non-linear assumptions and expanded rule-based assessment of architectures.

These foundational methodologies are insufficient in assessing the multi-function/multi-orbit WSF space system optimization problem for three primary reasons. First the optimization techniques identified by Matossian and Selva attempt to identify near-optimal architectures based upon the clustering of existing instruments and do not attempt to optimize sensor/instrument parameters to mission needs. If the conceptual designs of the existing sensors are not optimized for the specific mission then solutions are identified that may be far from optimal. Secondly, the GINA and MMDOSA "distributed" spacecraft conceptual design methodologies model satellite constellations of homogeneous spacecraft. The GINA methodology does not provide a method for space system conceptual design optimization. The MMDOSA methodology does not enable the optimization of heterogeneous satellite constellations associated with the multi-function/multi-orbit WSF optimization problem. Third none of the previous distributed satellite conceptual spacecraft design methodologies address techniques that enables model, physics, or requirement related constraints. Consequently, problems such as the

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Weather System Follow-on require a methodology that can address the unique aspects of

heterogeneous system solutions associated with multi-function/multi-orbit

disaggregation.

Methodology

A general methodology for the integrated analysis and optimization of disaggregated

system concepts was developed and described in [**39**]. An overview of this general

methodology is presented in Figure 12 and the methodology process steps are discussed

in sections 0, 0, and 0 that follow.
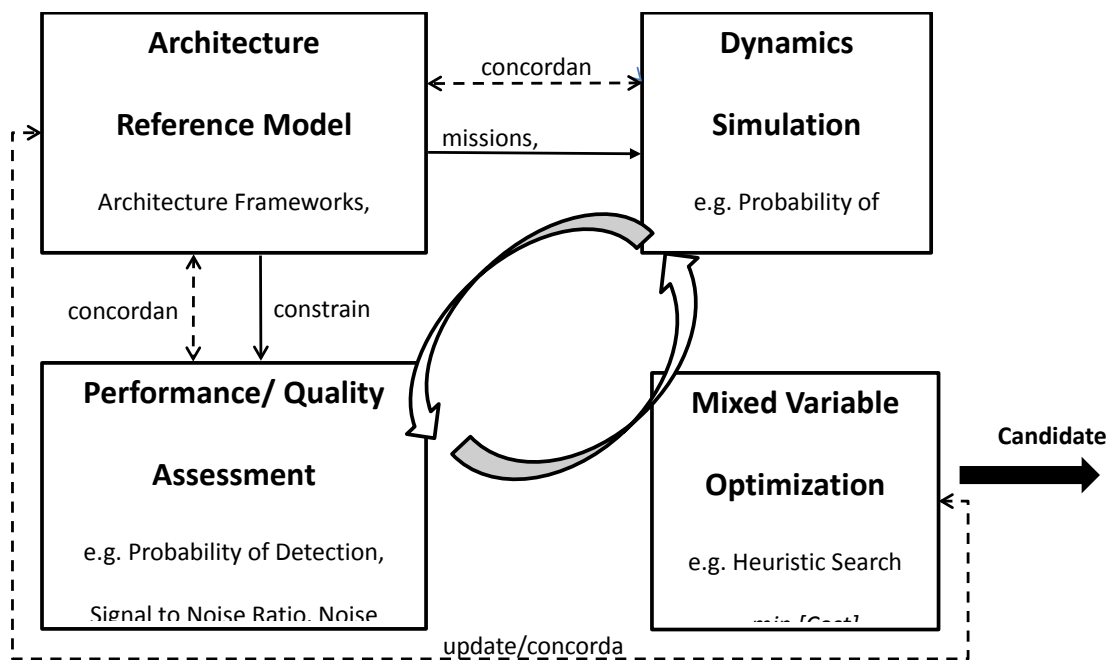
Figure 12. DISCO methodology overview.

DISCO is an integrated methodology intended to assist systems engineers in optimizing

conceptual system architecture solutions. Candidate logical architectures are developed

and documented in an architecture reference model based upon stakeholder needs and

system requirements. An optimization routine, using mixed variable optimization techniques, evaluates performance and dynamics measures while attempting to minimize objective functions associated with cost, schedule, performance, risk, and quality as applicable.

The general steps that comprise the DISCO methodology are:

1.   Develop reference architecture

2.   Develop integrated optimization and assessment models

3.   Evaluate results and update reference architecture

The DISCO methodology was applied to a single-function (fire-detection) multi-orbit disaggregation problem in [**39**]. The conceptual architectures for many practical space-based applications, such as weather, are required to perform multiple missions and functions. Several techniques used within the DISCO methodology must be tailored for the optimization of multi-function/multi-orbit disaggregation problems. These tailored techniques are highlighted in the following paragraphs using a conceptual DWSF system as an example.

Develop Reference Architecture

The conceptual reference architecture is an integrated model that summarizes the mission operations concept (including operator stakeholder needs, mission requirements, and constraints), Measures of Effectiveness (MOEs), draft system requirements and constraints, a logical architecture, and a mapping of the logical architecture to the logical/physical node architecture. This reference architecture should ideally be documented in a systems engineering modeling language such as SysML and be developed via a Model Based Systems Engineering (MBSE) tool using an MBSE

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methodology such as the Object Oriented Systems Engineering Method (OOSEM). The conceptual reference architecture should be only as detailed as necessary to identify the potential system type and technology concept trades.

Operations Concept, Stakeholder Needs, Mission Requirements/Constraints, MOEs, and draft system requirements

The operations concept includes "the way the system works from the operator's perspective" including needs, goals, and characteristics of the user community [13]. The operations concept as referred to in this methodology process step refers to MBSE products rather than the concept of operations document. The MBSE operations concept should identify stakeholders, stakeholder organization, and stakeholder needs via use cases and activity models. The mission requirements (also referred to as mission objectives), mission constraints, and draft system requirements/constraints should be modeled in SysML requirement diagrams. MOEs are the "operational measures of success that are closely related to the achievement of the mission or operational objective being evaluated, in the intended operational environment under a specified set of conditions" [13]. Principles for the use of effectiveness criteria are summarized in The Engineering Design of Systems and applicably include using "trade-offs to show the customer cost, performance, schedule, and risk impacts of requirements and solution variations" [40]. The DISCO methodology assumes that system affordability and system performance are identified MOEs. Schedule and Risk are other MOEs that are typically assessed through value modeling. For this paper, system affordability and system performance are identified as the applicable MOEs. The affordability MOE is addressed by structuring the optimization formulation to search for minimum estimated cost

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systems capable of meeting performance constraints. For the WSF example the system

performance MOE is assessed by the probability of detection for each required data

collection function (imagery, sea wind vectors, sea temperature, soil moisture, and space

weather data).   The MOEs should ideally be captured in mission level parametric

diagrams.

Logical Architecture, Function/System Traceability

A draft logical architecture should be developed according to pedigreed Systems

Engineering methods identified in [**41**]. The logical architecture identifies the system

functions derived from the mission objectives. The interactions between these functions

will likely be abstract at this point in the conceptual design process. Potential system

types are identified and defined in a block definition diagram. An example block

definition diagram for the WSF application is shown in Figure 13.

Develop Integrated Optimization and Assessment Models

An integrated optimization and assessment model is developed by first

determining the optimization formulation, then developing assessment models, then

developing a mixed variable optimization software routine with consistent model inputs

and outputs (e.g. design variables, constraint equation, linked variables, and calculated

constraint functions).

Optimization Formulation

The general DISCO optimization formulation has been extended to cover the

multi-function/multi-orbit disaggregation case. The corresponding extended general

DISCO mathematical optimization formulation is:

$$Find \ (x_i, y_{ij}) \ for \ i = 1 \ to \ n_1 \ and \ j = 1 \ to \ n_2$$

Which minimizes the function

$$f(\boldsymbol{x}, \boldsymbol{y}) = \sum_{i=1}^{n_1} c_i^{dev} x_i^{dev} + c_i^{prod} x_i^{prod} + c_i^{util} x_i^{util} + c_i^{supt} x_i^{supt} + c_i^{ret} x_i^{ret} \qquad [6]$$

Subject to the conditions

$$x_{iL} \le x_i \le x_{iU}$$
$$y_{ijL} \le y_{ij} \le y_{ijU}$$
$$\begin{cases} G_{ik}(\boldsymbol{x}, \boldsymbol{y}) \le 0 \; k = 1 \; to \; n_3 \; if \; i = 1 \\ G_{il}(\boldsymbol{x}, \boldsymbol{y}) \le 0 \; for \; l = 1 \; to \; n_4 \; if \; i \ne 1 \end{cases}$$
$$g_{im}(\boldsymbol{x}, \boldsymbol{y}) \le 0 \; for \; i = 1 \; to \; n_1 \; and \; m = 1 \; to \; n_5$$

where:

$$x_{io} = \{0,1\} \; for \; all \; i$$
$$\boldsymbol{x} = [x_1, x_2, \dots, x_{n_1}]^T : integer$$
$$\boldsymbol{y} = [y_1, y_2, \dots y_{n_2}]^T : continuous$$
$$c_{io}, c_i \; are \; functions \; of \; \boldsymbol{x} \; and \; \boldsymbol{y}$$

The term $f(\boldsymbol{x}, \boldsymbol{y})$ is the optimization objective function that is equivalent to the estimated

lifecycle cost, **c** represents the vector of calculated cost coefficient associated with the

number of systems of type i and the corresponding lifecycle category. The vector **x**

represents the number of systems of type i associated with the specific life cycle stages

(development, production, utilization/operation, support and retirement). The terms x_{iL},

x_{iU}, y_{ijL}, y_{ijU} represent integer lower and upper bounds and continuous upper and lower

bounds in turn.

The primary difference for multi-function versus multi-orbit optimization

formulations is related to the MOE constraints. The MOE constraint functions are

represented by the $G_{ik}(\boldsymbol{x}, \boldsymbol{y})$ terms. The MOE constraints should be measured at the

family of systems level. The combination of satellites must meet the MOE constraints

for the entire set of required mission functions. For the WSF example there are three

possibilities associated with meeting MOE constraints. First, a constellation of multi-

function satellites could meet the required collection capability. Secondly a constellation

of disaggregated small satellites could provide the required mission functionality. Finally,

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a combination or mix of multi-function and disaggregated small satellites could provide the full suite of required functionality. The optimization formulation is setup to account for this grouping of MOE constraints. Finally, the $g_{im}(x, y) \leq 0$ term represents model, performance, physical, or requirements constraints at the system, subsystem, or component level.

Assessment Models

Once the optimization formulation is complete, the applicable cost, performance, and dynamics models are developed. Numerous models could be used to assess potential Disaggregated Weather System Follow-on (DWSF) conceptual architectures. For disaggregated space systems two applicable cost models are identified. The Unmanned Space Cost Model (USCM) is applicable to large multi-function satellites and the Small Satellite Cost Model (SSCM) is used for small satellites. The latest version of the USCM only models estimated communication payload development and production costs. Consequently, the NASA Instrument Cost Model was used in conjunction with the USCM to estimate the development and production costs of payloads. These cost models are discussed in detail in [**1**].

Performance models vary significantly depending upon mission areas. For earth observation missions such as the WSF mission the primary system performance measures of performance can typically be derived to instrument sensitivity requirements such as Signal to Noise Ratio (SNR) or Noise Equivalent Difference Temperature (NEDT) at specified spatial or spectral sampling intervals. The source signal is commonly approximated using physics based equations such as Planck's equation.

Dynamics models generally fall into two categories for space systems: analytical approximations or numerical simulations. Analytic approximations can be used to estimate area coverage rates and area access rates. Numerical simulations can be used to accurately estimate constellation measures of performance such as revisit rates, percent coverage, and maximum coverage gap times for example. Previous applications of the DISCO methodology have demonstrated the use of analytic coverage and revisit rate approximations [42] and numeric simulation derived coverage and revisit rate calculation [39]. The analytic approximation technique enables much faster optimization routines but does not account for effects due to a spherical earth or satellite overlap. Optimization routines based upon numeric simulations take significantly longer to execute but enable accurate constellation orbit parameterization. The DWSF application discussed in the application section uses analytical approximation techniques to identify approximate solutions and then numeric simulations to finalize the orbit design and assess the identified near optimal solutions for revisit measures of performance.

Integration of Optimization Formulation and Assessment Models

The optimization algorithm execution function acts as the integration routine between the optimization formulation and the assessment models. The integration of the design variables, dependent variables, constraints, assessment module inputs, and outputs can be challenging for disaggregated space system optimization problems. SysML parametric diagrams can be used to aid in the organization of this step by identifying software modules and their associated inputs and outputs. For the WSF example the primary software modules are a genetic algorithm execution routine, an objective function module, a constraint function module, a cost model module, a dynamics module,

and a sensor performance module for each identified sensor type. The cost estimation module is integrated with the design variables based upon sizing of analogous sensors. The dynamics module calculates coverage or revisit constraints based upon a numeric dynamics simulator or analytical approximation techniques. The WSF example application uses analytical approximations to determine approximate solutions and then a numeric simulation is used to finalize the orbital design. The sensor performance module inputs sensor-related design variables such as satellite height, sensor view angle, and aperture diameter and outputs estimated performance metrics such as SNR or NEDT.

Evaluate Sensitivity of Optimization Results and Update Conceptual Reference architecture

Once the integrated optimization is executed, the results are assessed prior to convergence on a proposed conceptual architecture solution. Potential near-optimal solutions should be assessed for accuracy, fitness over identified local optimal solutions, and possibly sensitivity to requirements and stochastic parameters. The system architect should first verify the accuracy of the solution. This accuracy assessment should ensure that bounds and constraints were properly modeled. Secondly, the optimization routine should be executed across numerous trials, as heuristic optimization techniques are not guaranteed to provide global minimum solutions. If numerous optimization routines are executed with a random uniformly distributed initial population and minimal variations exist in the solutions, some confidence is gained in the solution for the given model assumptions. Finally, if the converged solution is heavily dependent upon the impact of variable parameters, a sensitivity analysis should be performed to determine the impact that parameter variations have on the results. Once adequate analysis of the results is

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complete, the design variables and calculated parameter estimates are updated in the reference architecture. Newer integrated MBSE tools should be able to automate this update. An example of the updated block definition diagram for the DWSF application is shown in Figure 18.

Application

The DoD needs a cost-effective responsive follow-on to the DMSP program. The Congressional Budget Office (CBO) conducted a study in 2012 assessing the options for modernizing military weather satellites. This report identified options for a WSF architecture that would provide space-based data to cover significant gaps in the future DoD weather enterprise caused by the cancellation of NPOESS and DWSS. The CBO report proposed three potential options defined by the inclusion of various legacy sensors on a single defense satellite in a single early morning orbit. The CBO report identified that an approach based upon distributing instruments amongst multiple satellites was possible. Several potential advantages of this multi-function, multi-orbit disaggregation were identified, including: smaller, simpler easier to build satellites, greater flexibility in deploying and replacing satellites, and greater flexibility to place sensors in orbits in which they are best able to carry out their mission. The CBO report stated that the "primary disadvantage of the distributed approach is that it might cost more than the single-satellite approach, depending on the specific configuration of the satellites". However, the CBO did not conduct a quantitative analysis of this "distributed" option. This paper provides this missing analysis, by applying the DISCO methodology to

determine cost-effective Disaggregated Weather Satellite Follow-on (DWSF) options and

make a comparison to traditional solutions of Large Multi-Function (LMF) satellites.

Weather System Follow-on (WSF) Reference Architecture

This section documents the WSF conceptual reference architecture. The

reference architecture is depicted with SysML diagrams that identify WSF stakeholder

needs, mission objectives, measures of effectiveness, initial system requirements, a

candidate logical and physical node architecture, and a draft mapping of primary system

functions to the candidate logical nodes. The Department of Defense (DoD) stakeholders

need a space-based, global, cost-effective, responsive, weather data sensing capability.

The mission objectives include providing functionality for

- the collection of cloud imagery and characterization,
- theater weather imagery,
- sea surface wind vectors (speed and direction),
- sea surface temperature
- soil moisture,
- and space weather measurement (ionospheric density, scintillation, charged particles, and electric field).

The measure of effectiveness for a conceptual WSF system was Probability of Detection

for each of these listed objectives under given conditions (i.e. clear weather, cloud-free

weather, or all-weather). The system requirements were derived by the authors through

the identification of potential gaps in weather data provided by the existing DoD systems

such as DMSP and key mission requirements previously identified in the National Polar-

orbiting Operational Satellite System (NPOESS) Integrated Operational Requirements

Document version 2 (IORD-II). Additionally, specific sensitivity requirements for SNR

and NEDT were derived by comparing consistent instrument sensitivity requirements and

instrument specification provided on previously developed imagery payloads in [**43**] and

previously developed microwave payloads in [**44**]. The corresponding system requirements are summarized in Table 4.

The cancellation of the NPOESS and DWSS programs has created the potential for significant gaps in DoD weather data collection capabilities. These potential gaps fall into the primary areas of imagery revisit, sea surface wind vector and surface temperature measurement, soil moisture content measurement, and space environmental monitoring. The collection gaps are primarily caused by the cancellation of the NPOESS and DWSS programs. There is a reduced number of satellites in the JPSS constellation versus the planned NPOESS constellation resulting in longer revisits for all weather data collections. The JPSS constellation does not include a microwave instrument that is able to detect sea surface temperature and wind vectors or soil moisture in cloudy conditions. Additionally, the JPSS concept does not include space environmental monitoring instruments. These readily identifiable gaps and the associated requirements from the NPOESS IORD-II were used to identify system requirements critical for a conceptual WSF system. The identified system requirements sourced from the IORD-II are summarized in Table 4 [**45**]. The requirements identified in Table 4 are a subset of the requirements associated with 56 Environmental Data Records identified in the IORD-II. The measurement bands and sensor performance SNR and NEDT requirements were obtained from references [**43**,**45**] and [**44**].

Table 4. WSF system requirements.

	Coverage area	Resolution	Refresh	Timeliness	Accuracy (mapping)	Accuracy (measurement)
Imagery						
Weather imagery	global	.4 km (nadir) .8 km (edge)	4 hours (avg revisit)* 6 hours (max revisit)	90 mins	1km (nadir) 3km (edge)	SNR 119 (L=22) (.64± .05µm) NEDT 2.5 (T=270K) (3.74±.38µm)
Sea Surface						
Wind speed (Clear)	global (ice-free)	20km (nadir)	6 hours	90 mins	5km	2 m/sec or 10%* NEDT .7 (305K) (19.3±.4 GHz)
Wind direction (Clear)	global (ice-free)	20km (nadir)	6 hours	90 mins	5km	20 degrees (>5m/s) NEDT .7 (305K) (19.3±.4 GHz)
Temperature (clear)	global	1 km (nadir)* 1.3 km (edge)	6 hours	90 mins	1 km (nadir) 1.3 km (edge)	uncertainty= .5 degrees C* NEDT=.396 (T=270K) (3.7±.18µm)
Temperature (all weather)	global	40 km(edge)	6 hours	90 mins	5 km	NEDT=.7 (305K) (19.3±.4 GHz)
Soil Moisture*						
Moisture content (clear)	global	1 km (nadir) 4 km (edge)	8 hours	90 mins	1 km 5 km	10% uncertainty (skin layer -.1cm) SNR 119 (L=22) (.64±.05µm)
Moisture content (cloudy)	global	40 km (nadir) 50 km (edge)	8 hours	90 mins	1 km 5 km	20% uncertainty (skin layer -.1cm)* NEDT .7 (305K) (19.3±.4 GHz)
Space Environment Monitoring						
Ionospheric density & scintillation	global	100 km	NA	90 mins		10^5 cm^{-3} or 30% .1 (amplitude),.1 radians (phase)
Charged Particles Electric field	LEO	Local	NA	90 mins	NA	15% (50 KeV to 4 MeV) 3 mV per meter (0+/- 150 mVm^{-1})

Note: Key Performance Parameters identified in the NPOESS IORD are identified by an *.

Once the mission needs/objective and system requirements are established candidate logical architecture options capable of meeting these needs/objectives and requirements are established for the WSF system. The potential system types are identified via a block definition diagram displayed in Figure 13. This figure demonstrates the mix between previously developed systems (such as the candidate launch vehicles) and logically defined systems such as the large multifunction and small imaging system. The parameters for the previously developed systems are already specified. The parameters for the logically defined systems will be estimated via optimization. The system numbers highlighted in Figure 13 are associated with the

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system type identifier in the optimization formulation. The association between blocks

also identifies the unknown relationship for conceptual systems. For example the space

system and ground system is identified as composition (a part of) relationship with the

WSF block because the WSF system is defined by the space system and ground system

blocks. Alternatively, the generalization relationship is used between the satellite type

and the WSF space system block because each satellite type is only potentially part of the

WSF space system concept definition. The optimization routine will identify which

satellite types are included in the definition of the WSF system along with the estimated

parameters for each system type. Likewise the potential launch vehicles are identified as

a potential generalization of the WSF mission enterprise until specific launch vehicles are

chosen as part of the mission architecture.
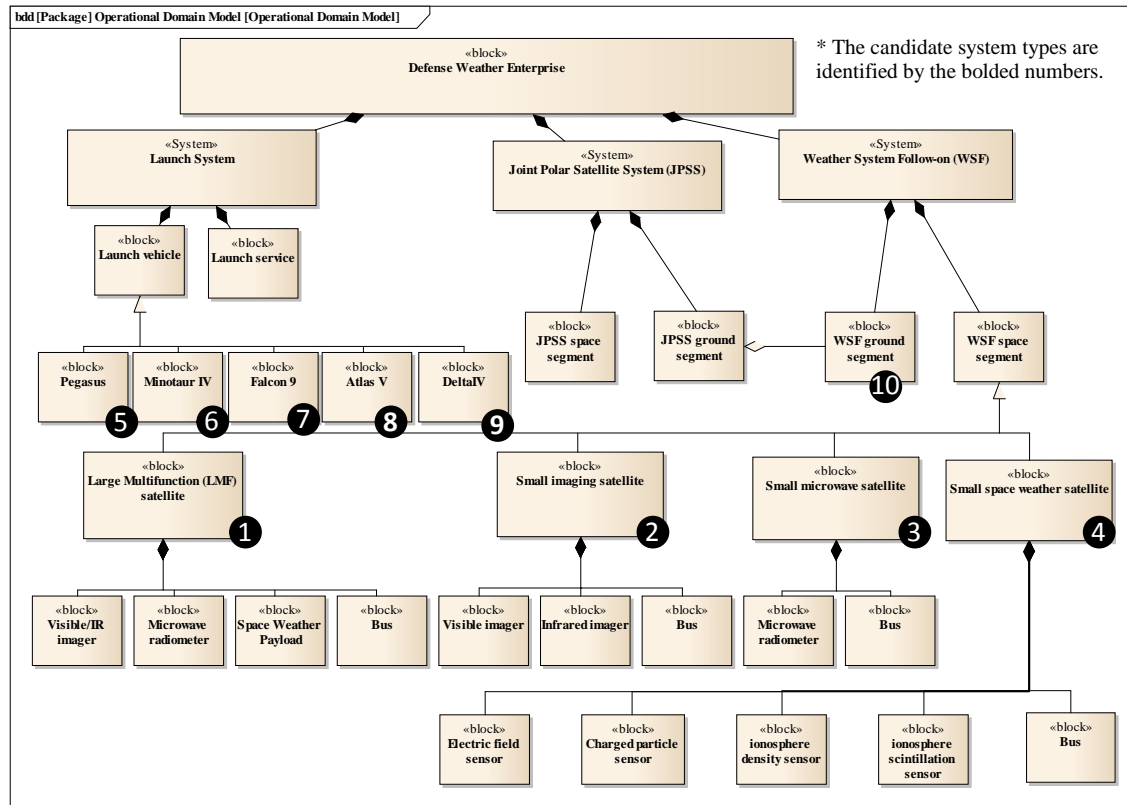
Figure 13. Example Logical Architecture Decomposition.

Once the potential system types are identified in the reference architecture then

mission level functions are identified and allocated to candidate system types. This

allocation is ideally shown in a SysML activity diagram. The functional allocation

depends upon the system type identification. For the WSF application two potential

allocations are possible. First all of the system functions can be allocated to sensors on a

large-multifunction satellite. Secondly, mission functions can be allocated to small

focused function satellites. Combinations of these allocations are possible however for

simplicity only these two functional allocation strategies were assessed. The large

satellite WSF functional allocation is displayed in Figure 14.

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act [Package] Operational Domain Model [Operational Domain Model]				
Large Multi-function Imaging Sensor	Collect imagery data (visible)	Collect imagery data (mid-wave IR)	Collect soil moisture content data (Clear)	Determine Sea Surface Temperature (Clear)	
Large Multi-function microwave sensor	Collect Imagery data (All-weather)	Collect Sea Surface Wind Speed data	Collect sea surface wind direction data	Collect sea surface temperature data (All Weather)	Collect soil moisture content data (Cloudy)
Large multi-function space weather sensor	Collect ionospheric density data	Collect ionospheric scintillation data	collect electric field data (LEO)	collect charged particle data (LEO)	

Figure 14. Activity diagram depicting WSF large spacecraft functional allocation.

Alternatively, the system function allocation for an example disaggregated system is depicted in Figure 15. The mission functions are allocated to separate small satellites that contain small functionally-related payloads. The functions could be further disaggregated among single function satellites. However, the functional disaggregation summarized here was chosen based upon functions that are provided using synergistic instrument/technology types. For example microwave radiometers have been demonstrated to provide ocean wind speed, wind direction, surface temperature, and soil moisture with similar sensor performance requirements. Additionally, the small visible imagery sensor and small mid-wave infrared (IR) sensors could be disaggregated further to separate satellites. However, soil moisture algorithms a dependent upon precise co-registration of visible and infrared measurements for determining soil moisture content in clear conditions [46]. Consequently the decision was made to disaggregate the visible and mid-wave IR sensors, but not disaggregate them to separate satellites. The DISCO methodology enables a trade study between these disaggregation techniques to determine which is more cost effective. The allocation of mission functions to logical nodes

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(conceptual design types) completes the reference architecture step and enables the

subsequent optimization formulation and assessment model development.
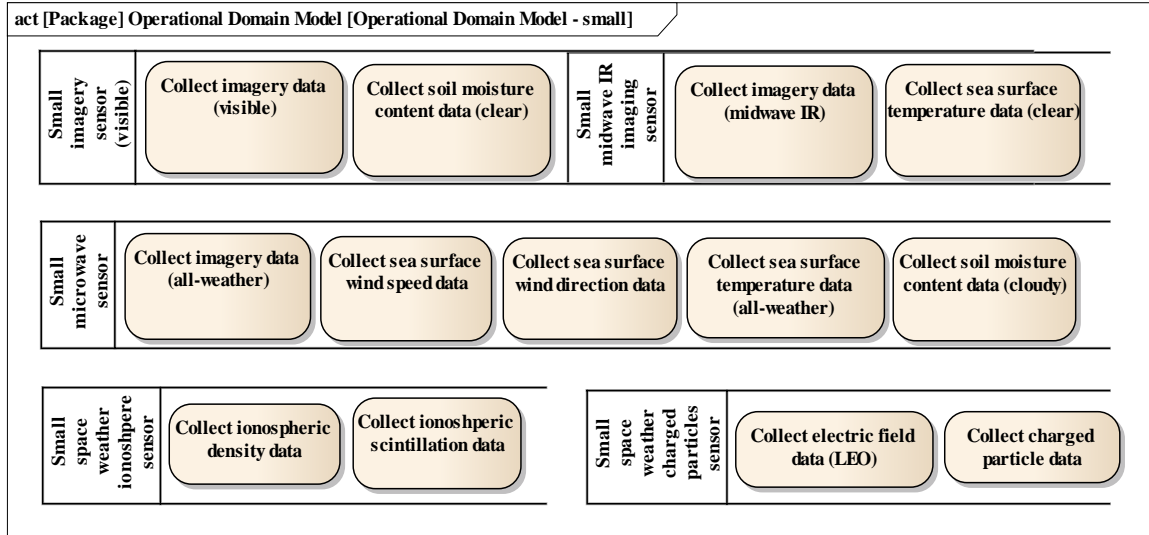
Figure 15. Activity diagram depicting WSF small spacecraft functional allocation

Weather System Follow-on (WSF) Integrated Optimization and Assessment Models

The integrated optimization and assessment models for the WSF conceptual

architecture problems consist of an optimization formulation that aims to minimize cost

subject to performance constraints, unmanned (large) and small satellite cost assessment

models, dynamics coverage models, sensor performance models, and a genetic algorithm

global optimization routine that integrates the optimization model with the assessment

models.

<div align="center">

Optimization formulation

</div>

The optimization formulation for a disaggregated WSF conceptual design

problem is consistent with the general multi-function multi-orbit optimization

formulation presented in the methodology section of this paper (Equation 6). It is

assumed that the greatest value system is the minimum estimated life cycle cost system

that meets threshold requirements. Consequently the objective function is defined for WSF as:

$$f(x,y) = \sum_{i=1}^{n_1} c_i^{dev} x_i^{dev} + c_i^{prod} x_i^{prod} + c_i^{util} x_i^{util} + c_i^{supt} x_i^{supt} + c_i^{ret} x_i \qquad [7]$$

where the estimated satellite development cost coefficient (c_i^{dev}) and production cost coefficient (c_i^{prod}) are calculated using the associated satellite cost models discussed in the subsequent section of this paper. The development costs for launch vehicles are assumed to be zero because previously developed launch systems are expected to be used and the production costs for launch vehicles are assumed to be equal to the average launch vehicle costs provided in Table 11-23 of [1] times the number of launch vehicles required. The development cost for the ground system is assumed $1.2 Billion for the system integration and data processing software development derived from the cost estimates provided in [33]. Satellite operations and data dissemination for current military weather satellites are performed by the NOAA Environmental Satellite Operations Control Center (ESOCC) and National Environmental Satellite Data and Information Service (NESDIS) systems. It is assumed that this operational relationship will remain and thus the development and production costs associated with the satellite operations and data dissemination components and facilities were assumed zero ($0). The estimated utilization cost coefficient (c_i^{util}) includes the cost to operate the WSF constellation. The Fiscal Year 2014 presidential budget submission includes a budget of $50 Million per year to operate all NOAA environmental satellites, including POES, GOES, and JPSS [31]. Accordingly, a conservative assumption was made that the cost to operate the constellation of WSF satellites would be at most $50M per year. The WSF

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life cycle costs were assessed for 18 years assuming an initial capability in 2020 and

extended operations through 2037. Additionally, it is assumed that operations costs are

primarily fixed and not highly dependent upon the number of supported satellites.

Anecdotally the authors personal knowledge confirms that the operations scale for large

constellations such as IRIDIUM, GPS, and Planet Labs Flock are on the same scale, if

not smaller that small constellations of large multi-function satellite systems such as the

Space Based Infrared System (SBIRS) or Advanced Extremely High Frequency (AEHF)

system. Publically releasable cost data justifying this assumption was not readily

available at the time of this paper submission. The estimated cost to support a system

(c^{supt}) is assumed to include the cost to produce replacement satellites and their

associated launch vehicles ($c^{replace}$) and the cost to sustain the system (c^{sust}). Thus the

support cost coefficient can be calculated using the following equation, $c_i^{supt} =$

$c_i^{replace} + c_i^{sust}$,where $c_i^{replace} = c_i^{prod} * (\frac{mission\ duration}{t_{replace}})$, and $t_{replace}$ is the assumed

satellite replacement time. The estimated cost to replace a ground system is assumed to

be zero because a ground system will be sustained rather than replaced during the mission

duration. The estimated cost to sustain a satellite is assumed to be zero because on-orbit

servicing is assumed to be infeasible and thus a satellite will be replaced versus sustained.

The fixed yearly estimated ground system sustainment costs were assumed to be $22.2

Million per year based upon derivations from the provided cost estimates in [**33**].   The

time to replace as small satellite was assumed to be 6 years and the time to replace a large

multi-function satellite was assumed to be 9 years. The assumed 6 year replacement time

for a small satellite was based upon a case study from small satellite developer Surrey

Satellite Technologies LTD (SSTL) that showed "an average Mean Time To Failure (MTTF) for their satellites of 6.4 year, yet the average design life was only 2.1 years" [1]. The assumed 9 year replacement time for a large multi-function satellite was based upon the 9 year satellite replacement time assumed in [33]. Thus the estimated cost to support (c^{supt}) the WSF system for the planned 18 year mission duration from 2020 to 2037 would include the cost to replace and launch each small satellite constellation twice and each large multi-function satellite constellation once plus a total of $400 Million for ground system sustainment over the 18 year mission life. This simplified technique for determining sustainment costs does not take into account the relatively large capability loss and associated risk related to a large multi-function satellite failure relative to a small satellite failure. Further research is planned on techniques to assess the impact of stochastic failure rates on disaggregated system optimization. Once the objective function formulation is established the next step in developing the optimization formulation is establishing the design variables.

The design vector for the WSF optimization problems consists of variables for binary development system inclusion, satellite planes, satellites per plane, satellite orbital height, sensor aperture diameter, sensor view angle, max vertical cell size, number of launch vehicles. These design variables along with their corresponding symbols and associated applicable system types are summarized in Appendix B of this article.

Table 5. WSF design variable summary

Design vector variable	symbol	Applicable systems	Variable type	Bounds Lower Limit→LL Upper→UL	Units
Development system in architecture	x^{dev}	i=1-9	binary	LL=0 UL=1	(#)
number of satellite planes	n_{planes}	i=1-4	integer	LL=1 UL=10	(#)
number of satellites per plane	n_{spp}	i=1-4	Integer	LL=1 UL=10	(#)
Satellite orbital height	h_{sat}	I=1-5	Real	LL=200 UL=varies	(km)
sensor aperture diameter	D_a	i=1-4	Real	Cost model dependent	(m)
sensor view angle	θ_{sensor}	i=1-4	Real	Geometry dependent	(degs)
horizontal sample interval at edge of service	HSI_{eos}	i=1-3	Real	Requirement dependent	(m)
number of launch vehicles	n_{lv}	i=5-9	Integer	LL=0 UL=10	(#)

The objective function value varies indirectly based upon the identified design variables via dependent variable equations. For example the estimated development cost of a system is calculated by multiplying the development cost coefficient ($\mathbf{c}^{dev}$) by the development system architecture inclusion variable ($\mathbf{x}^{dev}$). The development cost coefficient ($\mathbf{c}^{dev}$) for satellite system types is indirectly related to the D_a, θ_{sensor}, and HSI_{eos} through mass, power, and data rate calculations discussed in the appendices. The estimated satellite system production costs are determined by multiplying the estimated production cost coefficient ($\mathbf{c}^{prod}$) by the number of production satellites ($\mathbf{x}^{prod}$). The production cost coefficient ($\mathbf{c}^{prod}$) for satellite system types is also indirectly related to the D_a, θ_{sensor}, and HSI_{eos} through mass, power, and data rate calculations discussed in the appendices. The number of production satellites ($\mathbf{x}^{prod}$) is calculated using the equation

$x_i^{prod} = x_i^{dev} * n_{planes} * n_{spp}$ for i=1 to 4. The cost per production launch vehicle is assumed to be the average cost as described in the preceding section and the number of production launch vehicles is equal to n_{lv} such that $x_i^{prod} = n_{lv}$ for i=5 to 9. Once the WSF optimization formulation design variables are identified the next step is to identify the optimization constraints. The constraints for the WSF system are dependent upon the system type and the performance requirements, a summary identified in Table 6.

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Table 6. WSF constraint summary

Variable	Symbol	Applicable system	Constraint	units
Probability of detection	P_d	i=1,{2,3,4}	>99	%
Probability of signal detection	P_s	i=1-4	>99	%
Probability of coverage	P_c	i=1-4	>99	%
Satellite mass	m_{sat}	i=1-4	<=/>= cost model limits	kg
Payload mass	$M_{payload}$	i=1-4	<=/>= cost model limits	kg
Payload power	$P_{payload}$	i=1-4	<=/>= cost model limits	W
Payload data rate	$DR_{payload}$	i=1-4	<=/>= cost model limits	kbps
sensor view angle	θ_{sensor}	i=1-4	> Instantaneous Field of View (IFOV)	radian
Earth Central Angle	ECA	i=1-4	< Earth angular radius	radian
Elevation angle	€	i=1-3	> .35 (min geometric elevation angle)	radian
horizontal sample interval at edge of service	HSI_{eos}	i=1-3	> diffraction limited ground sample distance	m
vertical sample interval at edge of service	VSI_{eos}	i=1-3	> diffraction limited ground sample distance	m
horizontal cell size at nadir	HCS_{nadir}	i=1,2	< maximum required cell size at nadir	m
vertical cell size at nadir	VCS_{nadier}	i=1,2	< maximum required cell size at nadir	m
horizontal cell size at edge of service	HCS_{eos}	i=1-3	< maximum required cell size	m
vertical cell size at edge of service	VCS_{eos}	i=1-3	< maximum required cell size	m
total number of launch vehicles	N_{lv}	i=5-9	> total number of satellite planes	#
total lift capacity	LC	i=5-9	> total mass of satellites	kg

The mission level constraint is identified by the MOE probability of detection (P_d). Probability of detection is estimated by multiplying the probability of signal detection (P_s) by the probability of coverage (P_c). The P_d constraint is assumed to be 99% for all cases. The probability of signal detection is assumed to be 100% if the minimum performance constraints (i.e. SNR or NEDT) are met. The probability of coverage for the associated refresh time is estimated as the percent coverage for the associated coverage time. The MOE constraint is calculated as one value for a large multifunction satellite or the aggregate of the MOE constraints for all of the small satellites. The space vehicle system constraints include minimum and maximum mass limits identified by the corresponding cost model. Payloads are also constrained by minimum/maximum mass, power, and data rate limits associated with the NASA Instrument Cost Model or mass limits for the small satellite cost model. The sensors are constrained by a maximum earth central angle associated with a view angle greater than the maximum earth central angle. Sensors are also constrained by a minimum elevation

beyond which the vertical component of an image cell causes difficult to correct imagery and measurement errors. Sensors are constrained by the minimum horizontal/vertical sample interval determined by the diffraction limit. Sensors are also constrained by the max cell size at nadir and edge of service (EOS) defined by the system requirements. The sensor sizing is also constrained by a minimum and maximum aperture ratio. There are two primary launch vehicle constraints. First the total lift capacity of the launch vehicle must be greater than the total mass of the spacecraft. The lift capacity is currently assumed as a set mass limit for sun-synchronous orbit for a low earth orbit. The model is currently being updated to model maximum lift capacity for a sun-synchronous orbit via a non-linear regression of the lift capacity vs. orbital height (h) from the launch vehicle users guides. Additionally, the total number of launch vehicles must be greater than the total number of satellite planes in the architecture.   The launch vehicle constraint formulation is based upon techniques identified in appendix B of [**38**]. The complete optimization formulation is presented in appendix B of this article. Once the optimization formulation is fully identified the appropriate assessment models are developed.

Assessment Models

The DISCO methodology uses the combination of integrated parametric cost models and physics/geometry based dynamics/performance models. The estimated satellite development cost and production costs are calculated using existing satellite cost models including the Unmanned Satellite Cost Model (USCM), the NASA Instrument Cost Model (NICM), and the Small Satellite Cost Model (SSCM). Estimated satellite

development and production costs are calculated according to the methods discussed in

[**1**]. Satellite development costs are calculated according to the following equation:

$$C_{sat}^{dev} = C_{bus}^{dev} + C_{pl}^{dev} + C_{ia\&t}^{dev} + C_{program}^{dev} + C_{age}^{dev}$$ [8]

where the estimated development cost for a satellite is denoted C_{sat}^{dev}. The production

costs are calculated using the following equation:

$$C_{sat}^{prod} = C_{bus}^{prod} + C_{pl}^{prod} + C_{ia\&t}^{prod} + C_{program}^{prod} + C_{LOOS}^{prod}$$ [9]

The definitions, assumptions, and cost estimating relationships for each of these cost

components are detailed in appendix B of this article0.

Dynamics Assessment Model

Now that the top level cost estimation models are documented than the top-level

dynamics models are established. The primary dynamics model used for the WSF

conceptual design is based upon Probability of coverage (Pc) equation related to the

system refresh requirements as derived from chapter 10 of reference [**1**]. For this paper

Pc is estimated using analytical estimation techniques to enable conceptual design space

analysis. A simulation approach to more accurately estimate Pc or revisit rates directly is

discussed in [**39**]. For the WSF model Pc is estimated using the following equation for a

line scanning or push-broom sensor.

$$Pc = \frac{area\ covered}{global\ area} \approx \frac{\left(ACR_{avg}\left(\frac{km^2}{sec}\right) * \frac{3600sec}{hr} * T_{\text{refresh}}\ (hrs) * x_i\right)}{510,000,000(km^2)}$$ [10]

$$ACR_{avg} = \frac{K_A(sin(SW))}{P} * (1 - O_{avg}) * DC$$ [11]

where ACR_{avg} is the average area coverage rate, $T_{refresh}$ is the dwell time for the

instrument, x_i is the number of systems of type i with a particular instrument, K_A is a

constant equal to 2.556 x 10^8 for area in km^2, SW is the swath width for the instrument, P is the orbital period, O_{avg} is the average swath overlap, and DC is the duty cycle of the instrument [1]. A typical average swath overlap of .2 was assumed and a duty cycle (DC) of 1 was assumed.

Payload Performance Assessment Models

The performance models for WSF are primarily physics and geometry based models. The performance assessment models are specific to the function and technology types. Sensor performance is estimated by calculating the estimated SNR or NEDT. SNR is calculated using methods outlined in [1] using the following equation:

$$SNR \sim \frac{N_e}{N_t} \qquad [12]$$

where N_e is the estimated number of signal electrons and N_t is the total estimated number of noise electrons. NEDT is also estimated using methods outline in [1] and estimated to the first order using the equation:

$$NEDT \sim \frac{N_t}{\Delta N} \qquad [13]$$

where N_t is the total number of noise electrons and ΔN is the increase in number of estimated signal electrons associated with an increase in signal temperature of 1 degree Kelvin. Performance assessment models are further detailed in appendix B of this article.

Analyzing the WSF Optimization Results and Updating the WSF Reference Architecture

The WSF optimization was implemented using the MATLAB™ (industry standard) genetic algorithm. An initial population of 100 randomly generated solutions was created. The mutation rate was set to 0.2 and the convergence criteria was set to a

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maximum of 100 generations or 20 generations with less than \$1K estimated life cycle cost difference between generations. The optimization was executed for 10 trials with a relative minimal variation in the objective function. Each final solution was assessed for model accuracy and constraints. The best of the 10 solutions was chosen as the converged solution. This converged solution is summarized and assessed in the subsequent results section of this paper.

The DISCO methodology enables a system architect to perform requirements trades. The impact on Life Cycle Cost (LCC) can be estimated by varying refresh, resolution, coverage, or performance requirements, as well as executing the optimization routine multiple times. To demonstrate this method the critical performance requirement Ocean Surface Wind Vector (OSWV) revisit was traded. A trade was conducted between estimated LCC and estimated OSWV revisit.   Estimated refresh time ($T_{refresh}$) closely approximates the average revisit time for an optimized Walker constellation.   The results of this trade are summarized in Figure 16. The estimated refresh time was adjusted in one hour increments from the threshold requirement of 6 hours to the objective requirement of 1 hour. Five trials were executed for each increment. The result was a near exponential increase in estimated LCC. The results show that the number of satellites and estimated LCC increases dramatically above a refresh of 4 hours. An architect could use such trade study results to negotiate mission requirements with stakeholders to determine whether the increase in performance justifies the estimated increase in LCC. This analysis assumes that all other constraints and parameters are held constant. Due to the complex design space, it is necessary to vary one constraint requirement at a time in conducting these types of trades using the DISCO methodology.

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Sea Surface Wind Vector Refresh Trade

($B, #small microwave satellites, #Minotaur IV LVs)

$y = 7.8747x^{-0.364}$
$R^2 = 0.9937$

($7.98,30,13)
($5.94,16,19)
($5.29,10,14)
($4.87,10,13)
($4.33,6,10)
($4.11,4,6)

Estimated LCC ($B)

Estimated Refresh Time (hrs)
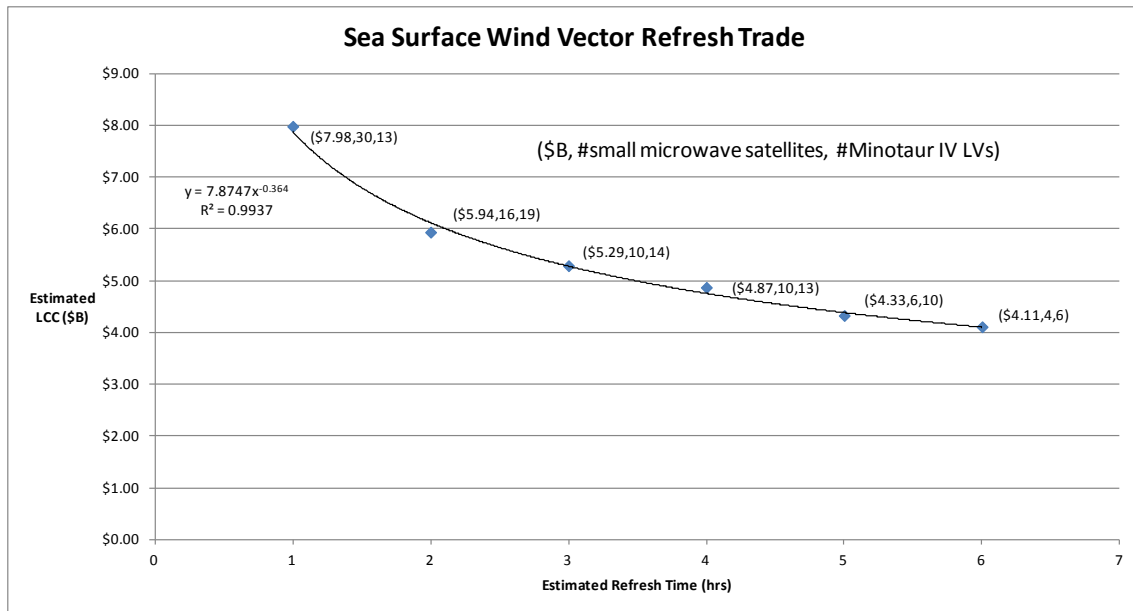
Figure 16. Example sea surface wind vector refresh trade study analysis using the DISCO methodology.

Results

Initial Solution

The identified minimum estimated life-cycle cost WSF conceptual solutions consists of a total of 8 small satellites in a family of systems with the NOAA/NASA JPSS spacecraft. This 8 satellite constellation solution consists of 2 small imaging satellites, 4 small microwave satellites, and 2 space weather satellites. Six Minotaur Launch vehicles were identified as part of this solution (one Minotaur 4 launch vehicle was identified to deploy each set of small imaging satellites and a space weather satellite, and one Minotaur 4 for each small microwave satellite. A graphical depiction of the initial satellite constellation is displayed in Figure 17.
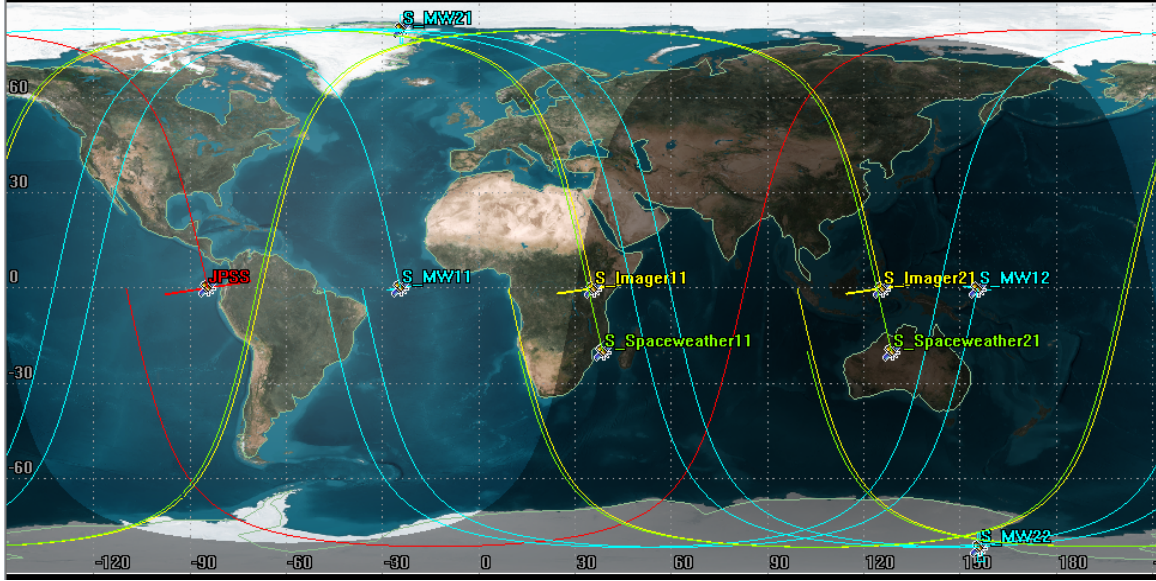
Figure 17. Optimized WSF constellation.

Analysis of the solutions was performed by modeling the candidate architectures in a dynamics simulator as walker-delta constellations in order to assess average and maximum revisit times. The requirement for refresh represents the maximum value of the local average over the set of all locations in the area of interest (i.e global area) [**45**]. The visible imager constellation consisting of one JPSS spacecraft and two small imagers had an average revisit across 1148 data points at 6 degree intervals of 2.33 hours which is better than the required 4 hour revisit time for imagery. Additionally, 98.7% of the grid points have a revisit time of less than 4 hours which is better than the required 75% that should have a revisit time of four hours or less. The average maximum revisit time is 3.93 hours which is less than the required maximum revisit time of 6 hours. The average revisit time for the microwave sensor is 6.25 hours for 1148 equally spaced points on the earth separated by 6 degrees. This is less than the required refresh for soil moisture of 8 hours and just slightly above the required sea wind vector refresh rate of 6 hours.

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Additional analysis is planned to use numerical simulation directly for the dynamics model rather than the approximate analytical techniques used for this case and this method should provide further refined optimization solutions.

The updated reference architecture block definition diagram associated with the solution is displayed in Figure 18. This updated block definition diagram displays the estimated parameters associated with the optimized satellite and instrument types necessary to meet the identified requirement in the most cost effective manner. The update of this block defintion diagram is currently a manual process but an on-going effort is underway to develop techniques to automatically update these values via executable parametric diagrams. The overall calculated satellite cost estimates appear reasonable when compared to analogous systems. For example the estimated development cost of the small microwave satellite with a .8 meter antenna is $119 Million. The Quickscat wind vector microwave scatterometer with a 1 meter dish cost approximately $98M in 2002 which is inflation adjusted to $131.1 Million 2010 dollars [47]. The development cost of the small imaging sensor with a .014 m visible sensor and a .032 m infrared sensor is calculated at $18.4 Million. The cost to develop the Bi-spectral Infrared Detector with similar specifications and an additional long wave infrared sensor was developed for $15 Million Euro in 2003 which is approximately $25.2 Million dollars after currency conversion and adjustment for inflation to 2010 dollars. [48] Cost data for the SENSE cubesats was not publically availible, however the approximated development cost of $4.97 million is a conservative cost estimate for historical 3U cubesats. The space weather satellites have masses at the lower limit of the

SSCM and it has been proposed that cubesat specific cost models should be developed to more accurately estimate cubesat development and production costs.

Once the WSF optimized conceptual architecture solution was identified using the DISCO methodology a comparative analysis was performed to determine the potential benefits obtained via a DISCO optimized Disaggregated Weather Satellite Follow-on (DWSF) architecture. The results of this comparative analysis are summarized in subsequent section.

Comparison of Optimized Solution with Previously Identified WSF Concepts

In 2010 the U.S. Congressional Budget Office identified potential options for modernizing military weather satellites. This report assessed the estimated cost for space-based weather systems based upon the inclusion of existing sensors on large multi-function satellites. The report assessed three conceptual spacecraft options. The first option consisted of a satellite with the Visible Infrared Imaging Radiometer Suite (VIIRS) payload that is currently on-orbit aboard the SUOMI NPOESS Preparatory Program (NPP) satellite, the MIS sensor based upon a sensor design developed by the Naval Research Lab for the NPOESS spacecraft, and the Space Environment Monitor-NPOESS (SEM-N) payload. The second option consisted of spacecraft with Advanced Very High Resolution Radiometer (AVHRR), MIS, and SEM-N payloads. The third option consisted of AVHRR, Microwave Imager/Sounder and AMSU-A [**33**]. All three options presented in this CBO report assumed that the military would transition from two satellites (one in an AM and another in a Mid-AM orbit) to a single AM orbit. This transition would not meet the needed data refresh rates identified by the weather stakeholders. Additionally, the AVHRR instrument included in option 2 and option 3

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would not provide the needed imagery horizontal cell size identified by the stakeholders. Option 3 also does not provide ocean surface wind speed, wind direction, or temperature provided by the DMSP satellite and identified as a DoD Key Performance Parameter (KPP) by the military weather stakeholder community. A significant effort was made to compare WSF options that meet critical military weather needs while providing a fair comparison between the DISCO optimized conceptual architecture and the previously assessed WSF options.   Accordingly the CBO option one was extrapolated to include 2 satellites (AM and mid-AM) to meet military revisit threshold requirements. The estimated life-cycle costs for this solution were then estimated using the same model assumptions as the DISCO optimized WSF constellation using the appropriate USCM and NICM CERs. The CBO option#1 derived option is essentially identical to the previous DWSS program and is hereafter referenced as the DWSS option accordingly. The life cycle cost comparison between the DWSS architecture concept and the Disaggregated Weather Satellite Follow-on (DWSF) Concept is summarized in Table 7. This LCC comparison also includes conservative estimates for the number of satellites required to replace the small satellites versus the large satellites. A more detailed breakout of the LCC components is provided in appendix B of this article. The CBO LCC estimates were based upon cost information provided by the NPOESS program. These CBO estimates are within the standard error for the USCM estimated satellite development and production costs.

bdd [Package] Design Model [Design Model]

«block»
Weather Satellite Follow-on (WSF) Enterprise

«block»
Launch System

«block»
Joint Polar Satellite System (JPSS)

«System»
Weather Satellite Follow-on (WSF) System

«block»
Minotaur 4
{18}
«Property»
Estimated cost : $K = 22000

«block»
Launch service

«block»
JPSS Space Segment

«block»
JPSS Ground Segment

«block»
WSF Ground Segment

«block»
Disaggregated WSF (DWSF) Space Segment

«block»
Small space weather satellite
{6}
«Property»
Production satellites : # = 1
Replacement satellites : # = 4
Analogous satellite : Satellite = SENSE
Estimated development cost : $K = 4972
Estimated production cost : $K = 2296
Estimated mass : kg = 21
Exists in architecture : True
Orbital height : km = 988
Orbital inclination : degrees = 98.6
Development satellites : # = 1

«block»
Small microwave satellite
{12}
«Property»
Estimated development cost : $K = 119654
Estimated production cost : $K = 53164
Development satellites : # = 3
Analogous satellite : Satellite = Quickscat
Production satellites : # = 3
Replacement satellites : # = 8
Estimated mass : kg = 383
Exists in architecture : True
orbital height : km = 523
orbital inclination : degrees = 98.6

«block»
Small imaging satellite
{6}
«Property»
Replacement satellites : # = 4
Orbital height : km = 988
Orbital inclination : degrees = 98.6
Analogous satellite : Satellite = Bi-spectral Infrared Detector
Estimated development cost : $K = 18483
Estimated production cost : $K = 8289
Estimated mass : kg = 81
Exists in architecture : True
Development satellites : # = 1
Production satellites : # = 1

«block»
bus

«block»
bus

«block»
bus

«block»
Ionosphere scintillation sensor
properties
analogous sensor = CTECS

«block»
Electric field sensor
properties
mass = 1 kg
Power = 1.3 W
volume = .00041 m^3
analogous sensor = WINCS

«block»
ionosphere density sensor
properties
sensor-CTIP
mass = 1 kg
power = 3 W

«block»
charged particle sensor
properties
analogous sensor

«block»
microwave payload
{12}
«Property»
View angle : degrees = 41.9
HCSeos : m = 19635
Analogous payload : Payload = Seawinds
Estimated development cost : $K = 26097
Estimated power : W = 144
Estimated production cost : $K = 10438
Estimated data rate (DR) : kbps = .22
Estimated mass : kg = 118
Reflector diameter : m = .83

«block»
Visible imaging payload
{6}
«Property»
Estimated power : W = 18
Estimated data rate (DR) : kbps = 2617
Aperture diamter : m = .0077
View angle : degrees = 48
Estimated development cost : $K = 1354
HCSnadir : m
Estimated production cost : $K = 541
HCSeos : m = 590
Estimated mass : kg = 8.4
Analogous payload : Payload = WAOSS

«block»
Infrared imaging payload
{6}
«Property»
Estimated production cost : $K = 1070
Estimated mass : kg = 16.6
Estimated power : W = 108
Estimated data rate : kbps = 150
Aperture diameter : m = .024
View angle : degrees = 54
HCSeos : m = 1262
Analogous payload : Payload = HSRS
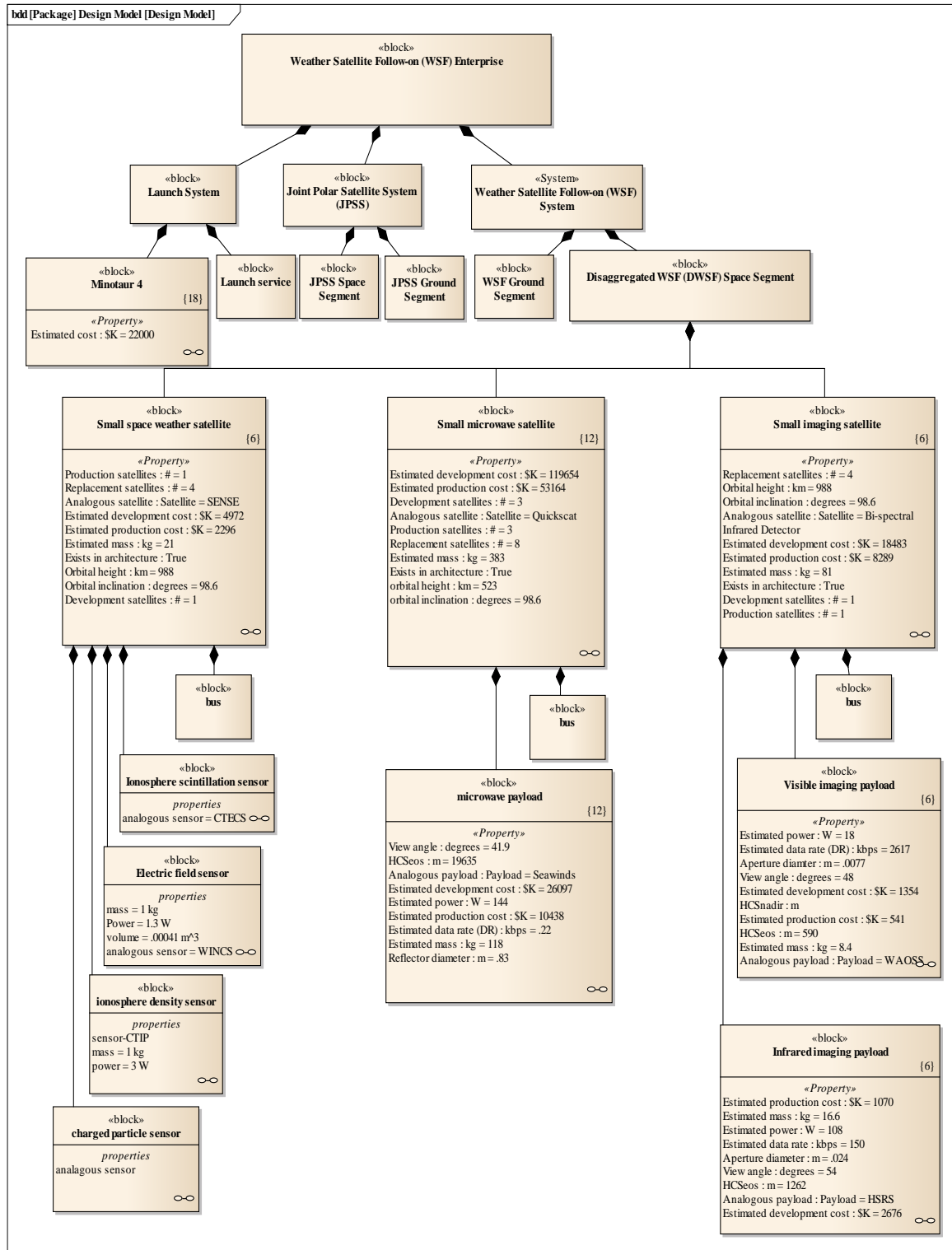Estimated development cost : $K = 2676

Figure 18. Updated reference architecture block definition diagram.

Table 7. Estimated Life Cycle Costs (LCC) for optimized Disaggregated Weather System Follow-on Solution compared to the Defense Weather Satellite System (DWSS) reference.

	DWSS USCM ($M)	DWSF solution SSCM ($M)
Total Satellite development cost	$ 1,342	$ 148
Total Satellite production cost	$ 829	$ 168
Total Satellite replacement cost	$ 1,659	$ 468
Total Ground system integration, data processing sw	$ 1,200	$ 1,200
Total Launch (Deployment) cost	$ 688	$ 396
Total Storage cost	$ 140	$ 400
Total Operations cost	$ 900	$ 900
Total Ground system sustainment / engineering support	$ 400	$ 400
Total Retirement cost	$ 30	$ 30
Total estimated Life Cycle Cost (ROM)	$ 7,188	$ 4,110
Total estimated Life Cycle Cost (ROM) standard error*	$ 1,285	$ 75

*Note: The standard error was calculated only for cost elements estimated by a cost model (spacecraft development and production costs). CBO option#1 is extrapolated from the cost estimates provided in [**33**]. For comparison purposes, the satellite costs for the CBO option was estimated using the corresponding USCM model with results identified in the second column of estimates. The CBO solution was identified by determining the number of satellites necessary to meet the WSF requirements identified previously. The corresponding life-cycle costs are identified in the third column of estimates. The DWSF solution also meets the WSF requirements identified in the preceding section. All lifecycle cost estimates are adjusted to 2010 year dollar.

According to this comparative analysis there is potentially significant ($3 Billion) LCC savings realized by adapting a DISCO optimized DWSF conceptual architecture solution. Additionally, the estimated LCC for the DWSF solution ($4.1 Billion) is less than lower cost CBO options 2 ($4.9 Billion) and options 3 ($4.4 Billion) that did not meet critical DOD mission needs including refresh/revisit rate, measurement cell size, and in the case of option 3 critical functionality (ocean wind speed and wind direction). The estimated life cycle cost savings are the result of multiple efficiencies gained through the optimization and disaggregation methods. The VIIRS and MIS payloads identified for the DWSS satellite were designed for a larger set of joint civil and military (NPOESS) requirements than those required for the military WSF mission. The expanded set of requirements led to larger, more complicated, and thus costlier payload

conceptual designs. For example one of the driving requirements for the VIIRS payload was the need to accurately detect ocean color. The ocean color requirement (which is not a defense related requirement) led to a larger, higher power, higher data rate VIIRS imagery payload. This complex imagery payload design was carried over to the DWSS concept. By optimizing the payload conceptual design criteria to the subset of requirements needed for the WSF mission the imagery and microwave payload mass, volume, power, data rate and consequently estimated cost is reduced significantly. Additionally, the multitude of required environmental data types also led to a single aperture multi-spectral (VIIRS) imagery payload design. The beam-splitters, multi-spectral filters, and multiple reflective surfaces required to implement an aggregated multi-spectral payload led to significant signal losses. A larger aperture with correspondingly larger mass, power, and data rate was thus required for DWSS to meet the SNR and NEDT constraints. The reduction of losses garnered by disaggregating the visible and infrared sensors (without beam splitters, multi-spectral filters, and reflective surfaces) enables a significantly smaller aperture and consequently more economical imagery payloads for the DWSF small satellites. Smaller payloads also enable smaller satellites and consequently more cost effective launch vehicles. Additional cost efficiencies are gained by fine tuning the constellation design to the requirements. Two large multi-function satellites are required to meet the revisit requirements given the assumed DWSS orbital altitude of 840 km with the existing payload specifications. An architecture based upon small spacecraft allows a better fine tuning of revisit timelines and thus enhanced economic efficiencies.

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Conclusion

An adaptation of the Disaggregated Integral System Concept Optimization (DISCO) methodology was made to handle multi-function/multi-orbit problems, as exemplified by the Weather System Follow-on (WSF) concept. The application of DISCO indicates that the methodology is able to address real-world disaggregation problems with efficiencies in personnel and resources, when compared with traditional manually intensive engineering approaches. These traditional approaches often only examine a few solutions, typically evolutionary from past architectures, without an attempt for overall system optimality. Literature identified several space constellation optimization approaches, but these only addressed distributed multi-orbit homogeneous solutions, orbit optimization for single satellites, or multi-function solutions constrained to existing sensors. While offering a strong foundation, none of these extant methods have been formulated to handle the integrated sensor/payload (multi-function) and multi-orbit problem. Interestingly, the DISCO methodology found a potential, cost-effective solution for the WSF program. This solution consisted of 8 satellites (2 small imaging satellites, 4 small microwave satellites, and 2 small space weather satellites), and 6 Minotaur launch vehicles. This solution has an estimated $3Billion lifecycle cost savings over a large multi-function DWSS approach, which should be further assessed.

Chapter III Appendix A - Optimization formulation[3]

$$f(\pmb{x}, \pmb{y}) = c_1^{dev} x_1^{dev} + c_1^{prod} x_1^{prod} + c_1^{util} x_1^{util} + c_1^{supt} x_1^{supt} + c_1^{ret} x_1 + c_2^{dev} x_2^{dev}$$
$$+ c_2^{prod} x_2^{prod} + c_2^{util} x_2^{util} + c_1^{supt} x_2^{supt} + c_2^{ret} x_2 + c_3^{dev} x_3^{dev}$$
$$+ c_3^{prod} x_3^{prod} + c_3^{util} x_3^{util} + c_3^{supt} x_3^{supt} + c_3^{ret} x_3 + c_4^{dev} x_4^{dev}$$
$$+ c_4^{prod} x_4^{prod} + c_4^{util} x_4^{util} + c_4^{supt} x_4^{supt} + c_4^{ret} x_4 + c_5^{prod} x_5^{prod}$$
$$+ c_6^{prod} x_6^{prod} + c_7^{prod} x_7^{prod} + c_8^{prod} x_8^{prod} + c_9^{prod} x_9^{prod} + c_{10}^{dev} x_{10}^{dev}$$
$$+ c_{10}^{prod} x_{10}^{prod} + c_{10}^{util} x_{10}^{util} + c_{10}^{supt} x_{10}^{supt} + c_{10}^{ret} x_{10}$$

$$P_d \geq .99$$

$$s.t. \, G_2\big(x_{1,4,5}, y_{1j,4j,5j}\big) \geq .99 \rightarrow (Pd) \;\; Pd = Ps * Pc$$

$$0 \leq x_{1,1} \leq 10 \; (\text{\# satellite planes})$$
$$0 \leq x_{1,2} \leq 10 \; (\text{\# satellites per plane})$$
$$200 \leq y_{1,1} \leq 35178 \; (orbital\ height\ [km])$$
$$.04 \leq y_{1,2} \leq 1 \; (aperture\ diameter - imager\ [m])$$
$$0 \leq y_{1,3} \leq 65.66 \; (max\ nadir\ angle\ [degs])$$
$$.36 \leq y_{1,4} \leq 2 \; (aperture\ diameter - microwave\ [m])$$
$$0 \leq y_{1,5} \leq 65.66 \; (max\ nadir\ angle\ [degs])$$
$$400 \leq M_{sc} \leq 5127 \; (USCM\ mass\ model\ limits\ [kg])$$
$$\lambda \leq ECA_{limb} \; (\text{earth central angle limit – imager, microwave [degs]})$$
$$\epsilon \leq 20 \; (minimum\ elevation\ angle - imager, microwave\ [degs])$$
$$CS_{nadir} \leq 400 \; (reqd\ nadir\ cell\ size[m] - imager)$$
$$CS_{eos} \leq 800 \; (reqd\ edge\ cell\ size[m] - imager)$$
$$SI \geq GSD_{diff} \; (sample\ interval\ diffraction\ limit - imager)$$
$$SNR \geq 119 \; (required\ imagery\ sensor\ performance - visible)$$
$$NEDT \leq .396 \; (required\ sea\ surface\ temp\ sensor\ performance - infrared)$$
$$CS_{eos} \leq 20{,}000 \; (reqd\ edge\ cell\ size[m] - microwave)$$
$$SI \geq GSD_{diff} \; (sample\ interval\ diffraction\ limit - microwave)$$
$$NEDT \geq .7 \; (required\ sea\ surface\ wind\ sensor\ performance - microwave)$$

$$0 \leq x_{2,1} \leq 20 \; (\text{\# satellite planes})$$
$$0 \leq x_{2,2} \leq 20 \; (\text{\# satellites per plane})$$
$$200 \leq y_{2,1} \leq 35178 \; (orbital\ height\ [km])$$
$$.00154 \leq y_{2,2} \leq .0385 \; (aperture\ diameter - visible\ imager\ [m])$$
$$0 \leq y_{2,3} \leq 65.66 \; (max\ nadir\ angle\ [degs])$$
$$.0046 \leq y_{2,4} \leq .115 \; (aperture\ diameter - infrared\ imager\ [m])$$
$$0 \leq y_{2,5} \leq 65.66 \; (max\ nadir\ angle\ [degs])$$
$$20 \leq M_{sc} \leq 400 \; (SSCM\ mass\ model\ limits\ [kg])$$
$$\lambda \leq ECA_{limb} \; (\text{earth central angle limit [degs]-visible, infrared imager [degs]})$$

---

[3] Note that the optimization objective function is a non-linear and discrete function despite initial appearances. The estimated system cost terms $(c_i^{dev}, c_i^{prod}, c_i^{ops}, c_i^{supt}, c_i^{ret})$ are functions of the problem design variable vector $(\pmb{x})$ for satellite system types. Additionally, the system number terms $(x_i^{dev}, x_i^{prod}, x_i^{ops}, x_i^{supt}, x_i^{ret})$ are also functions of the problem design variable vector $(\pmb{x})$ and can only have integer values. The $x_{i,s}$ terms identified in the optimization formulation are system specific design variables included in the design variable vector $(\pmb{x})$. The $y_{i,s}$ terms identified in the optimization formulation are continuous system specific design variables included in the design variable vector $(\pmb{x})$.

$$\epsilon \leq 20 \ (minimum\ elevation\ angle - visible, infrared\ imager\ [degs])$$
$$CS_{nadir} \leq 400 \ (reqd\ nadir\ cell\ size[m] - imager)$$
$$CS_{eos} \leq 800 \ (reqd\ edge\ cell\ size[m] - imager)$$
$$SI \geq GSD_{diff} \ (sample\ interval\ diffraction\ limit - imager)$$
$$SNR \geq 119 \ (required\ imagery\ performance - visible\ sensor)$$
$$NEDT \leq .396 \ (required\ sea\ surface\ temp\ performance - infrared\ sensor)$$
$$CS_{eos} \leq 20{,}000 \ (reqd\ edge\ cell\ size[m] - microwave)$$
$$SI \geq GSD_{diff} \ (sample\ interval\ diffraction\ limit - microwave)$$
$$NEDT \geq .7 \ (required\ sea\ surface\ wind\ performance - microwave\ sensor)$$

$$0 \leq x_{3,1} \leq 20 \ (\#\ satellite\ planes)$$
$$0 \leq x_{3,2} \leq 20 \ (\#\ satellites\ per\ plane)$$
$$200 \leq y_{3,1} \leq 35178 \ (orbital\ height\ [km])$$
$$.2 \leq y_{3,2} \leq 1 \ (aperture\ diameter - microwave\ [m])$$
$$0 \leq y_{3,3} \leq 65.66 \ (max\ nadir\ angle\ [degs])$$
$$20 \leq M_{sc} \leq 400 \ (SSCM\ mass\ model\ limits\ [kg])$$
$$\lambda \leq ECA_{limb} \ (earth\ central\ angle\ limit\ [degs]\text{-}microwave\ [degs])$$
$$\epsilon \leq 20 \ (minimum\ elevation\ angle - microwave\ [degs])$$
$$CS_{eos} \leq 20{,}000 \ (reqd\ edge\ cell\ size[m] - microwave)$$
$$SI \geq GSD_{diff} \ (sample\ interval\ diffraction\ limit - microwave)$$
$$NEDT \geq .7 \ (required\ sea\ surface\ wind\ performance - microwave\ sensor)$$
$$x_4 = 2 \ (assumed\ 2\ space\ weather\ satellites\ in\ constellation)$$

$$0 \leq x_5 \leq 40 \ (bounds\ on\ \#Pegasus\ launch\ vehicles)$$
$$0 \leq x_6 \leq 40 \ (bounds\ on\ \#Pegasus\ launch\ vehicles)$$
$$0 \leq x_7 \leq 40 \ (bounds\ on\ \#Pegasus\ launch\ vehicles)$$
$$0 \leq x_8 \leq 40 \ (bounds\ on\ \#Pegasus\ launch\ vehicles)$$
$$0 \leq x_9 \leq 40 \ (bounds\ on\ \#Pegasus\ launch\ vehicles)$$
$$M_{sats} \leq LC_{LVs} \ (Total\ mass\ of\ satellites\ less\ than\ total\ lift\ capacity)$$
$$N_{planes} \leq N_{LVs} \ (Total\ \#\ of\ satellite\ planes\ less\ then\ \#\ of\ launch\ vehicles)$$

wh $$x_{io} = \{0,1\}\ for\ all\ i$$

ere

$$\boldsymbol{x} = [x_1, x_2, \dots, x_{n_1}]^T \ \text{x is an integer}$$

$$\boldsymbol{y} = [y_1, y_2, \dots y_{n_2}]^T \ \text{y is continuous}$$

c_{io} and c_i are functions of x and y

Chapter III Appendix B - Example sensor performance calculations

Sea Surface temperature

The table below provides an example of the sensor performance calculation method for

SST NEDT calculation. Similar calculations were completed for each sensor

performance requirement.

Reference Large satellite clear weather Sea Surface Temperature (SST) Mid-wave Infrared (MWIR) NEDT calculation as derived from Table 17-9 of [1]

Parameter	1 Large MF	units	equation
Orbital Altitude [h]	779967.01	m	
Orbit Period [P]	100.45	min	$P=1.658669E\text{-}4*(Re+h)^{(3/2)}$
Ground Track Velocity [Vg]	6.65	km/s	$Vg= 2*Pi*Re/P$
Node shift [ΔL]	25.18	deg	$deltaL=P/1436min*360deg$
Angular radius of the earth [ρ]	63.00	deg	$arcsin(Re/(Re+h))$
max earth Central Angle [λ_0]	27.00		
IR imager (VIIRS) - M12 Sea Surface Temp			
Range to the horizon [Dmax]		m	
Minimum Elevation Angle	20.00	deg	
Sensor look angle (nadir angle) [η]	51.83	deg	
elevation angle [Є]	28.08	deg	$ACOS(SIN(\eta)/SIN(\lambda_0))$
incidence angle [IA]	61.92		
Earth Central Angle [λ]	10.09	deg	
Slant Range [Rs]	1421713.00	m	
Swath Width [2*λ]	20.18	deg	$2*\lambda$
Max vertical cell size at edge	1300.00	m	
Max horizontal cell size at edge	1300.00	m	
Max vertical cell size at nadir	1000.00	m	
Max horizontal cell size at nadir	1000.00	m	
Diffraction limited GSD at Nadir	18.9030	m	$GSD\_diff\_nadir=h*\lambda/D$
Diffraction limited GSD at Edge	34.4561	m	$GSD\_diff\_nadir=R\_s*\lambda/D$
Specified Max along track GSD, [Yeos]	1195.45	m	
Along track Instantaneous Field of View [IFOV$_Y$]	0.0482	deg	$IFOV\_Y=(Y\_eos/R\_s)*(180/pi)$
Native eos cross track pixel resolution [Xlimit]	2539.66	m	
Number of cross track detector samples at nadir [X#]	2.00		$X\#=Xlimit/HCSeos$
Effective eos cross track pixel resolution [Xeos]	1269.83		$Xeos=Xlimit/X\#$
Cross Track Instantaneous Field of View [IFOV$_X$]	0.0482		
cross track ground pixel resolution [Xnadir]	655.84	m	$Xnadir=IFOVx*h*(pi/180)$
along track ground pixel resolution [Ynadir]	655.84	m	$Ynadir=IFOVy*h*(pi/180)$
# of cross track pixels [Zc]	2151.52	pixels	$Zc=2*\eta/IFOVx$
# of swaths recorded along track in 1 sec [Za]	10.14	swaths	$Za=Vg*1/Y$

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# of pixels recorded in 1 sec [Z]	2.18E+04	pixels	Z=Zc*Za
# of bits used to encode each pixel [B]	8.00	bits	parameter
Data Rate [DR]	0.17	Mbps	DR=Z*B*Nbands
# of pixels for whiskbroom [Nm]	32.00	pixels	parameter
Swath overlap	1.13		parameter
pixel integration period [Ti]	3.75E-04	seconds	(Y/Vg)*(Nm/O)*(#X/(2*Pi*h)
pixel read out frequency [Fp]	2663.38	Hz	Fp=1/Ti
detector time [Tdet]		seconds	
detector pixel width [d]	1.00E-05	meters	parameter
quality factor for imaging [Q]	1.10		parameter
operating wavelength [λ]	3.70E-06	meter	
focal length [F]	1.14	m	
aperature diameter [Da]	0.153	m	design variable
Edge of Service SNR Calculation			
Blackbody temp [T]	270.00	K	parameter
Operating Bandwidth [Δλ]	1.80E-07	m	parameter
Emissivity	1		
Emitted power density [Eλ]	300138.44 54	W/m^2-m-sr	$E(\lambda) = \left(\dfrac{2*pi*h*c^2*\epsilon}{\lambda^5}\right)*\left(\dfrac{1}{exp\left(c*\dfrac{h}{kT\lambda}\right)-1}\right)$
Blackbody spectral radiance [Lλ]	2.39E+04		L(λ)=E(λ)/(4*pi)
transmissivity of the atmosphere [τ]	0.90		Modtran estimated
Upwelling radiance [Lupi]	2.15E+04		Lupi(λ)=L_λ*τ (λ)
Integrated upwelling radiance [Lint]	3.87E-03	W/m^2/sr	Lint=∑Lupi(λi-λi+1)
radiated power /pixel [L]	5873.59	W/sr	L=Lint*X*(Y/X#)
input power [P]	5.32E-11	W	Pin=(L/h^2)*(D/2)^2*pi
Number of reflective surfaces	10		
Number of beamsplitters	1		
Number of optical filter interfaces	16		
Incidence angle [θ_inc]	1		
index of refraction [n]	1.35		
m	1		
spectral filter thickness [d]	1.37E-06		d=(m*λ)/(2*n)
Beta angle [β]	0.62		β=asin(sin(θ_inc)/n)
Varphi [φ]	5.108		φ=(4*pi*n*d)/(m*λ)
Etrans	0.970		
Filter reflectivity	0.500		
Eo	3.459		Eo=(1+(4* ρ)/(1-ρ)^2*sin(φ/2)^2
filter optical transmittance [τ_filter]	0.280		τ_filter=E_trans/E_o
optical transmission factor [τo]	0.04		
input power at detector pixel [Pd]	2.19E-12		Pd=Pin*τo
energy after integration [E]	8.24E-16		E=Pd*Ti/X#
# of available photons [Np]	1.53E+04		Np=E*λ/h*c
Quantum Efficiency [QE]	0.50		
# of electrons available [Ne]	7673.90		Ne=Np*QE
# of noise electrons [Nn]	87.60		Nn=Ne^.5
# of read out noise electrons [Nr]	25.00		
total # of noise electrons [Nt]	91.10		Nt=(Nn^2+Nr^2)^.5
Signal to Noise Ratio [SNR]	84.24		SNR=Ne/Nt
Dynamic Range (cold space) [DR]	306.96		DR=Ne/Nr
Required SNR	10.00	ratio	
Edge of Service NEDT Calculation (+1 deg K)			
ΔN	418.85	#	ΔN=Ne_new-Ne
NEDT	0.2229146 52	ratio	NEDT=Nt/ΔN
Required NEDT	0.396		

An optical system which collects mission data in multiple bands (such as the VIIRS payload) requires a relatively large aperture due to signal loss associated with adaptive optics, beamsplitters, and optical filters. Approximately 3% of an optical signal is lost per clear optics interface. Approximately 5% of an optical signal is lost per reflective optical interface. An optical signal is reduced by approximately 58% through a beam splitter. Additionally, measurement bands are typically produced via optical filters. The relative signal loss of an optical filter is dependent upon sensor view angle according to the following equations:

$$\tau_{filter} = \frac{E_{trans}}{E_o} \tag{14}$$

$$E_o(\theta) = (1 + \frac{4*\rho}{(1-\rho)^2}) * sin\left(\frac{\varphi}{2}\right)^2 \tag{15}$$

where Eo is the emissivity of the optical filter. ρ is the filter surface reflectance. φ is an angular function. Consequently these losses account partially for the larger aperture diameter required for a multi-band multi-function optical sensor (such as VIIRS) versus the single band HSRS imaging sensor on the Bi-spectral Infrared Detector. These optical loss estimates are derived from the AFIT multi/hyper spectral fundamentals course notes.

Sea surface wind performance model

Space based microwave radiometry sensors have been used extensively to determine sea surface wind speed and vectors. The empirically derived algorithm to estimate sea surface wind speed from microwave brightness readings is:

$$estimated\ wind\ speed\ \left(\frac{m}{s}\right) = 147.9 + 1.0969 * B_{19,V} - .4555 * B_{22,V} - 1.760 * B_{37,V} + .7860 * B_{37,H}$$

The algorithm has an accuracy <2 m/s if rain is not present and the required cell size and

NEDT meet the stated requirements. There is a correction for water vapor contamination

or high wind speeds [44]. Microwave transmittance over the ocean is dependent upon

sensor angle based upon angle of incidence according to the following equations:

$$\Gamma(\theta, v) = \left| \frac{\varepsilon_2 cos\theta_1 - \sqrt{\mu_2 \varepsilon_2 - \sin^2 \theta_1}}{\varepsilon_2 cos\theta_1 + \sqrt{\mu_2 \varepsilon_2 - \sin^2 \theta_1}} \right|^2 \qquad [16]$$

Where $\Gamma(\theta, v)$ is the vertically polarized microwave transmittance of a dielectric surface.

ε is the relative complex dielectric constant. μ is the relative magnetic permeability of

medium 2 (ocean salt water) [49]. This relationship was coded into the microwave SNR

and NEDT calculation functions.

Soil Moisture

 Soil moisture from the surface layer to a few millimeters can be assessed under sparse or

incomplete vegetation cover. For low density vegetation the equation for estimating soil

moisture is:

$$Soil\ moisture = .5 * API \qquad [17]$$

where:

$$API_{low} = 659.35 - 675.22 * T_{B(19,h)} \qquad [18]$$

$$B = \frac{T_{B(19,V)} + T_{B(37,V)}}{2} + \frac{T_{B(19,H)} + T_{B(37,H)}}{2} \qquad [19]$$

This estimating equation is accurate within ±10% volumetric soil moisture content

accuracy for the previously stated required cell size and NEDT [44].

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Cost model and cost comparison details

Large Multi-Function (LMF) satellite development costs are estimated using a combination of the USCM for satellite related cost estimates and the NICM for payload related cost estimates as discussed in chapter 11 of <u>Space Mission Engineering: The New SMAD</u> [1]. The USCM estimation is a summation of component costs according to the following equation:

The estimated development cost for a spacecraft bus is denoted as C_{bus}^{dev} for a payload is denoted as C_{pl}^{dev}. After inclusion of USCM Cost Estimating Relationship (CER) values the estimated equation to determine estimated large space vehicle development costs is:

$$C_{sv,large}^{dev} = (110.2M_{sc}) + (C_{pl}) + (.195(C_{sv} + C_{pl})) + .414(C_{sv} + C_{pl}) + (.944 * C_{sc})$$

[20]

The USCM only includes CER equations for communication satellites. Consequently the NICM was used to estimate the WSF payload costs. The NICM CER for an earth observation optical payload such as the WSF large satellite imager is: $C_{pl} = (1{,}163M_{pl}^{.328} * P_{pl}^{.357} * DR_{pl}^{.092})$ where C_{pl} is the estimated development cost of the optical payload in thousands of dollars (\$K), M_{pl} is the estimated mass of the optical payload in kg, and DR_{pl} is the estimated data rate of the payload in kbps. The mass and power of the payload is estimated using sizing relationships based upon sensor aperture ratio discussed in section 17.2.6 of [1]. The data rate is calculated for each payload based upon the equation $DR = Z * B * N_{bands}$ where Z is the number of pixels recorded in one second for a given sensor, B is the number of bits used to encode each pixel, and N_{bands} is the number of spectral bands recorded as described in table 17-9 of [1]. Likewise, the NICM estimated development cost for an active or passive microwave instrument is :

$$C_{pl} = 23{,}620 * M_{pl}^{.284} * P_{pl}^{.325} * DR_{pl}^{.09} * TRL_{pl}^{-1.296}$$

[21]

where Mpl is the mass of the microwave payload, Ppl is the power of the microwave payload, DRpl is the data rate of the payload, and TRLpl is the Technology Readiness Level of the payload based upon the NASA TRL scale.

For a large spacecraft the production cost is also estimated using USCM as documented in [1]

$$C_{sv,large}^{prod} = C_{bus}^{prod} + C_{pl}^{prod} + C_{ia\&t}^{prod} + C_{program}^{prod} + C_{loos}^{prod}$$

[22]

The estimated space system cost for a small space system is calculated using the Small Spacecraft Cost Model (SSCM) discussed in chapter 11 of [1].

The estimated development cost for a small space system is calculated as:

$$C_{ss,small}^{dev} = C_{bus}^{dev} + C_{pl}^{dev} + C_{ia\&t}^{dev} + C_{program}^{dev} + C_{age}^{dev} + C_{sw}^{dev}$$

[23]

Once the CER values are populated the corresponding equation is:

$$C_{ss,small}^{dev} = (1{,}064 + 35.5M_{sc}^{1.261}) + (.4C_{sc}) + (.139C_{sc}) + (.229C_{bus}) + (.061C_{bus}) + C_{sw}$$

[24]

IV. Stochastic Analysis Methods

Introduction

Today's space systems have far reaching impacts to U.S. Department of Defense (DoD) users globally. They provide a multitude of mission applications such as communications; global navigation and timing; precise weather and climate inputs; and global intelligence, surveillance, and reconnaissance. However, the systems that provide these capabilities can be complex, costly, and highly susceptible to technical risks [**4**]. It has been hypothesized that the "vicious circle of space acquisition" leads to space system architectures consisting of a relatively small number of large, complex, and expensive satellites that lack system-wide resiliency [**3**]. It has been proposed that this is driven in part by a low risk tolerance.

Disaggregating space system architectures has been identified as a strategy that has the potential to improve cost effectiveness and resiliency of future space system architectures. According to a recent Air Force Space Command report on disaggregation of space systems "disaggregating space architectures is one strategy to improve resiliency, offering a means to trade cost, schedule, performance, and risk to increase flexibility and capability survivability" [**50**]. However, the associated trade space is complex and highly mission specific. Methods for conducting such architectural trades represent a powerful and necessary capability for space system architects aiming to design cost effective and resilient space system architectures.

The aim of this paper is to document and demonstrate a potential methodology for conducting trades between cost-effectiveness, risk, and performance for candidate space system architectures. A disaggregated space system optimization methodology termed Disaggregated Integral System Concept Optimization (DISCO) is summarized as an effective system architecting tool. Catastrophic space vehicle and launch vehicle failures are identified as potential risks to space systems. The impact of space vehicle and launch vehicle failures due to adverse conditions are modeled as cost risk. The corresponding space vehicle and launch vehicle failure rates are modeled according to empirical Space Vehicle (SV) and launch vehicle (LV) reliability data. These methods enable the automated generation, assessment, and cost/risk optimization for a vast number of potential architectural alternatives. Explicitly, this paper aims to achieve the following three objectives.

1. Outline methods for incorporating probabilistic satellite and launch vehicle failure rates associated with disaggregated space system optimization problems

2. Demonstrate how these methods can be applied to an applicable disaggregated space system optimization problem (i.e. Weather System Follow-on WSF)

3. Determine how variations in risk weighting, failure rates, and performance requirements can be assessed to perform disaggregated space system trades between cost and risk.

The results indicate that, for the example application, the minimum cost disaggregated architecture solution is also the minimum risk solution. These architectures are also shown to be highly robust to large variations in launch vehicle and space vehicle failure rates.

Background

This article builds upon a series of articles describing an alternative methodology for modeling, assessing, and optimizing disaggregated space system conceptual designs. The methodology is termed Disaggregated Integral System Concept Optimization (DISCO). The general methodology was introduced and originally applied to a basic fire detection satellite concept design problem [**51**] [**52**]. Later, the DISCO methodology was tried on the Weather System Follow-on (WSF) mission using multi-function/multi-orbit disaggregation optimization methods [**53**] [**54**]. This paper documents an extension of the DISCO methodology to assess the impacts of stochastic satellite and launch vehicle failure rates on the proposed Disaggregated Weather System Follow-on (DWSF) architecture. These extensions utilize extant probabilistic satellite and launch vehicle failure models.

Space System Optimization

Significant research has been conducted on distributed space system optimization methods [**16**] [**17**] [**18**] [**19**] [**20**]. The DISCO methodology represents an advancement of these methods that is capable of simultaneously optimizing disaggregated space system architectural concepts characterized by multiple heterogeneous system types, payload functionalities, orbital parameters, and satellite sizing via Model Based Conceptual Design (MBCD) methods. A relatively small amount of research has been conducted on introducing stochastic parameters into distributed or disaggregated space system optimization methodologies. Selva introduced the concept of modeling satellite development cost risk based upon satellite subsystem Technology Readiness Level (TRL) [**20**]. This research introduced methods for modeling launch risk as a function of the

number of instruments placed on orbit and the perceived preference to solutions that are robust to single launch failures [20].

Jilla et al. estimated reliability of distributed satellite constellations using Markov Models [18]. These authors also incorporated reliability in a launch vehicle selection tool as cost risk [55]. The research in this paper extends Jilla's method of modeling launch vehicle failure risk to the broader disaggregated space system optimization problem. These extensions account for cost risk associated with the probability of failure across heterogeneous satellite constellations and heterogeneous launch vehicles.

Space Vehicle Reliability

Traditional space system engineering methods often model spacecraft reliability according to the cumulative probability of failure for "electronic parts, connections, and moving mechanical assemblies." However, "the historical on-orbit data do not match the reliability equation predictions" for several reasons [1]. First, these traditional reliability methods do not account for non-component related failures such as design flaws and workmanship errors. Second, assumed constant failure rates used by these traditional methods do not account for the fact that "once functioning, spacecraft life often far exceeds predictions" [1]. Consequently, we have chosen to model spacecraft failure rates based upon empirical on-orbit data vice traditional reliability analysis. A relatively recent series of space system reliability studies were published by Castet and Saleh. The impact of design life requirements on spacecraft design was synopsized in [56]. Weibull models were demonstrated to accurately model satellite reliability versus satellite on-orbit time [57]. Furthermore, satellite reliability was shown to vary according

to satellite mass categories using Weibull statistical models [**58**]. The resulting satellite

mass reliability models are thus adapted to the DISCO methodology.

Launch Vehicle Reliability

Historical analysis of launch vehicle failures has demonstrated that the overall

reliability of launch systems as a whole is 90 to 95% [**59**]. This relatively low reliability

represents a significant risk for space system conceptual designs. Traditionally launch

vehicle reliability is estimated by decomposing the launch system into its subsystems and

statistically calculating the probability of each failure mode. Alternatively, launch vehicle

reliability using Bayesian probability estimation techniques are summarized in [**60**]. The

Bayesian reliability estimation techniques have been successfully demonstrated to

accurately capture launch vehicle reliability and the associated error distribution for

launch vehicle families (i.e. system types) accounting for the relatively low success rate

for new launch vehicle types. The probabilistic reliability calculations used in this paper

utilize the Bayesian reliability estimation techniques with binomial distributions.

Monte Carlo Analysis

Monte Carlo analysis is a problem solving technique used to approximate the

probability of certain outcomes by running multiple trials while sampling stochastic

parameters. This technique is often used to assess the effect of probabilistic elements in

an operational systems model when the decision environment is comprised of many

random (stochastic) variables [**61**]. In the conceptual design of individual spacecraft,

Monte Carlo methods have been used to determine sensitivity of component reliability

[**62**], distributed architecture trade-space investigations [**18**] and assessment of satellite

swarm reliability [**63**]. In this paper, Monte Carlo analysis will be used to enable an assessment of failure rate distribution impacts on the optimal conceptual designs.

Methods

Early in the conceptual design process mission designers and system architects must "make decisions on a mission fulfillment approach using small satellites, large satellites, or a mixture of both" as described in [**1**]. Traditional methods of conducting space system conceptual architecture trades are often limited to the design, assessment, and improvement of a few candidate architectures. These traditional system architecting methods are potentially inadequate to effectively design, assess, and optimize the vast conceptual design space associated with disaggregated space systems. This design space is further complicated by stochastic parameters such as space vehicle and launch vehicle reliability. The DISCO methodology is a potentially powerful tool enabling effective analysis of this vast trade space. This methodology section consists of five parts. First, an overview of the DISCO methodology is presented. Secondly, extensions to the DISCO optimization formulation are proposed that account for satellite and launch vehicle reliability impacts. Third, a method for incorporating satellite reliability based upon Weibull distribution models is outlined. Fourth, a method for incorporating launch vehicle reliability based upon Bayesian probability model is introduced. Finally, Monte Carlo methods enabling the assessment of conceptual design impacts associated with the distribution of stochastic failure rates is introduced. These methods will form the basis for the analysis presented in the application and results sections of this article.

DISCO Methodology Overview

The primary motivation for the Disaggregated Integral System Concept

Optimization (DISCO) methodology is the enablement of improved system analysis and

optimized solutions across all disaggregation types (i.e. multi-orbit, multi-function,

hosted payloads, and fractionation). An overview of all potential logical decompositions

is presented in Figure 19. Figure 20 shows a general overview of the DISCO approach.

The general DISCO problem solving approach consists of the following components:

reference system architecture, dynamics models, performance assessment models, and

mixed variable optimization functionality.

The architecture reference model forms the basis of the disaggregated space

system optimization approach. The primary stakeholder needs, mission objectives,

system requirements, and logical/physical architecture artifacts are modeled in a MBSE

architecture tool. The architecture reference model is kept in concordance with

performance/quality assessment and dynamics simulations via engineering analysis. This

concordance may be maintained via an automated electronic means or through manual

manipulation as currently implemented. System requirements documented in the

architecture reference model (e.g. coverage, resolution, sensitivity, accuracy and revisit

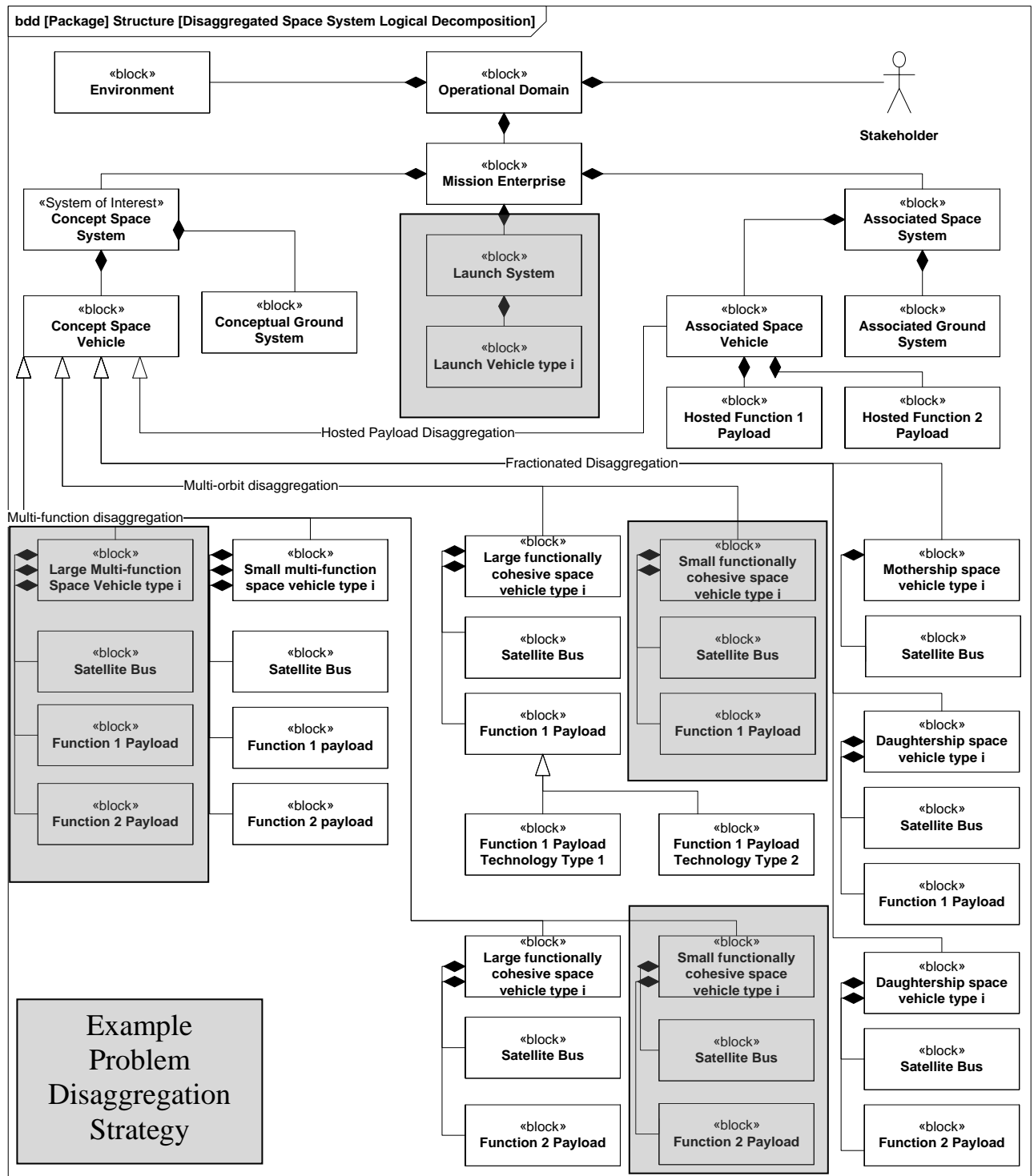rate) form the constraints of the performance assessment.

Figure 19. Disaggregated space system logical decomposition strategies summary
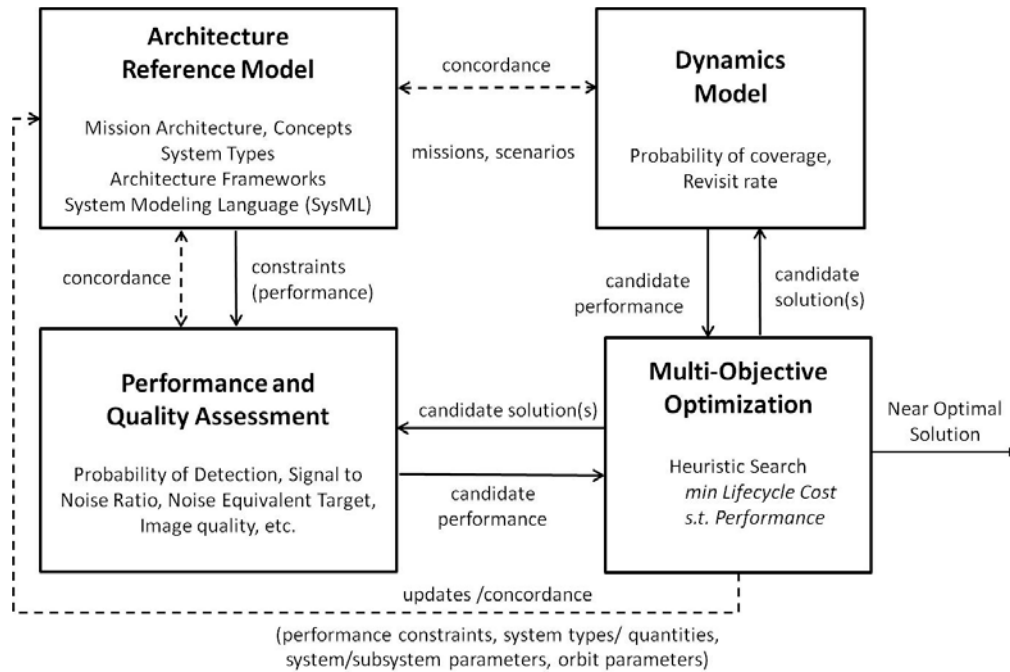
Figure 20. DISCO methodology overview

The performance assessment models consist of performance estimating equations, sizing equations, and cost estimating equations applied to candidate architectures. Candidate solutions (represented as individuals in the genetic algorithm) are evaluated and the estimated performance and cost of the solution are returned to the optimization routine. The dynamics model consists of a numeric simulation capability or analytic coverage estimating equations used to assess the dynamic performance of the conceptual system. The dynamics model inputs candidate solutions (individuals) and returns dynamics related performance measures (e.g. revisit rate). The optimization routine evaluates the fitness of each of the candidate solutions as well as the feasibility (e.g. constraint violations) of each of the candidate solutions. The optimization routine then outputs the best feasible candidate architecture for further evaluation.

The DISCO methodology assumes that the performance of disaggregated space architectures is dependent upon the type of systems, the number of systems, the

performance of each system, and the orbital dynamics of the constellation. The

optimization component outputs candidate near-optimal disaggregated space system

architectures in the form of a design variables that represent the number of systems

included in the architecture, the critical design variables (i.e. payload aperture diameter

and sensor view angle) and the constellation orbital parameters (i.e. orbital altitude).

These near-optimal solutions are assessed and evaluated. The candidate solutions and

corresponding calculated functions (i.e. satellite mass, volume, and power) are used to

update the reference architecture.

Optimization formulation

Previous DISCO optimization mathematical models were structured to minimize

estimated Life Cycle Cost [52] [53]. The previous formulation was expanded to enable

the minimization of Life Cycle Cost Risk (LCCR) or risk weighted cost (LCC plus

LCCR). This expansion enables the assessment of potential impacts from stochastic

variables such as space vehicle and launch vehicle failure rates. Consequently the

expanded DISCO optimization formulation is an extension of the standard Mixed

Variable Optimization (MV-OPT) outlined in [64]. The corresponding expanded DISCO

mathematical optimization formulation is[4]:

Minimize
$$f(\pmb{x}) = \omega_1 LCC + \omega_2 LCCR \qquad [25]$$

$$LCC = \sum_{i=1}^{n_1} C_i^{dev} x_i^{dev} + C_i^{prod} x_i^{prod} + C_i^{ops} x_i^{ops} + C_i^{sust} x_i^{sust} + C_i^{ret} x_i^{ret} \qquad [26]$$

$$LCCR = \sum_{i=1}^{n_1} CR_i^{dev} x_i^{dev} + CR_i^{prod} x_i^{prod} + CR_i^{ops} x_i^{ops} + CR_i^{sust} x_i^{sust} + CR_i^{ret} x_i^{ret} \qquad [27]$$

---

[4] Note that the optimization objective function is a non-linear and discrete function. The estimated system cost terms ($c_i^{dev}, c_i^{prod}, c_i^{ops}, c_i^{supt}, c_i^{ret}$) are functions of the problem design variable vector ($\pmb{x}$) for satellite system types. Additionally, the system number terms ($x_i^{dev}, x_i^{prod}, x_i^{ops}, x_i^{supt}, x_i^{ret}$) are also functions of the problem design variable vector ($\pmb{x}$) and can only have integer values.

subject to

$$h_i = 0, i = 1 .. n_2,$$
$$g_j \leq 0, j = 1 .. n_3$$
$$x_i \epsilon D_i, D_i = (d_{i1}, d_{i2}, \dots, d_{iq_i}), i = 1 .. n_d$$
$$x_i^{\text{dev}} \epsilon \{0,1\}$$
$$x_{iL} \leq x_i \leq x_{iU}, i = (n_d + 1) .. (n_d + n_c)$$

where

f is the optimization objective function

x is the design variable vector

ω is a weighting factor

LCC is the estimated system Life Cycle Cost

$LCCR$ is the estimated system Life Cycle Cost Risk

C is the calculated cost coefficient for system type i,

CR is the calculated cost risk coefficient for system type i

x_i^{dev} represents existence of system type i in an architecture

x_i^{prod} is the number of systems (type i) in the conceptual design

x_i^{ops} is the number of systems that require operations

x_i^{sust} is the number of sustainment systems required

x_i^{ret} is then number of systems that require retirement

h is an equality constraint equation

g is an inequality constraint equation

n_d is the number of discrete variable in the discrete set D

x_{iL} represents the design variable lower bound

x_{iU} represents the design variable upper bound

n_c is the number of continuous design variables

This design optimization formulation above is modeled to minimize the weighted

objective function of life cycle cost (LCC) and life cycle cost risk (LCCR). The term risk

weighted cost is established for the value associated with LCC plus LCCR where $\omega_1=1$

and $\omega_2=1$. The LCC and LCCR functions are broken up into the corresponding life cycle

phases (development, production, operations, sustainment, and retirement). The cost

coefficients are based upon cost models for the appropriate system type. These models

are summarized in more detail in the application section of this paper.

Satellite Reliability

Satellite/Space Vehicle (SV) reliability is modeled as cost risk and calculated

according to the following equation:

$$CR_i = P_{SVFi} * C_{SVFi}$$

[28]

where
CR_i is the calculated cost risk for SV type i
P_{SVFi} is the probability of failure for SV type i
C_{SVFi} is the estimated cost impact of an SV failure

An SV failure, in this context, is assumed to be a catastrophic satellite failure prior to the

end of the SV design life. The cost impact of an SV failure C_{SVFi} is assumed to be the

production cost of an on-orbit or ground spare SV. Likewise, the probability of an SV

failure is estimated according to the equation:

$$P_{SVF} \sim F_{SV}(t) = 1 - R_{SV}(t)$$

[29]

where
P_{SVFi} is the probability of failure for SV type i
$F_{SV}(t)$ is the SV failure rate at on-orbit time (t) in years (%)
$R_{SV}(t)$ is the estimated reliability of a space vehicle (%)

Satellite reliability has been estimated for catastrophic failures based upon empirical data.

This reliability analysis has been developed for large and small satellites [**58**].   The

reliability equations follow the standard Weibull equation format:

$$R_{SV}(t) = \exp\left(-\left(\frac{t}{\theta}\right)^{\beta}\right)$$

[30]

where
$R(t)$ is the reliability estimating equation
t is the time that the satellite is on-orbit (years)
β is the shape parameter (dimensionless)
θ is the scale parameter (years)

This reliability equation is used to estimate the failure rate for the corresponding space

vehicle types identified in the DISCO problem formulation.

Launch Vehicle Reliability

Launch Vehicle (LV) reliability is modeled as cost risk and calculated according to the

following equation:

$$CR_i = P_{LVFi} * C_{LVFi}$$

[31]

where
CR_i is the calculated cost risk for launch vehicle type i
P_{LVFi} is the probability of failure for launch vehicle type i
C_{LVFi} is the estimated cost impact of a launch vehicle failure

The estimated cost impact of a launch vehicle failure includes the estimated production

cost of the launch vehicle plus the cost of the satellites on the failed launch vehicle. The

probability of a launch vehicle failure is estimated according to the equation:

$$P_{LVF} \sim F_{LV}(t) = 1 - R_{LV}(t)$$

[32]

where
P_{LVFi} is the probability of failure for launch vehicle type i
$F_{LV}(t)$ is the LV failure rate for launch attempt (t) (%)
$R_{LV}(t)$ is the estimated reliability of a launch vehicle

Launch vehicle reliability is estimated based upon Bayesian estimation techniques using

the following equation from [**60**]:

$$R_{LV}(t) = \frac{k + 1}{n + 2}$$

[33]

where
R(t) is the estimated reliability of the launch vehicle
k is the number of successful launch events
n is the number of launch trials

These reliability modeling techniques are used to demonstrate how risk modeling can be incorporated into a concept architecture optimization application in the subsequent application section of this article.

Monte Carlo Analysis Methods

Traditional steps in a Monte Carlo Procedure include the following: formalize the system logic, determine the probability distribution, develop the cumulative probability distribution, and perform the Monte Carlo process [61]. The DISCO methodology employs these four steps to assess how stochastic parameter distributions affect the minimum risk weighted cost (LCC plus LCCR) solutions. First, the system logic is defined via the DISCO approach and mathematical optimization formulation. Secondly, the probability distributions of the stochastic variables are identified using empirical data. For example, the LV and SV failure rate data are ascertained from the empirical launch and on-orbit failure rates. Third, the cumulative probability distribution is developed for the output. For example, the cumulative weighted LCC plus LCCR distribution is calculated in the example below. This enables a system architect or program decision maker to understand the likelihood of program cost and cost risk values based upon the empirical reliability distribution of the various system types. Finally the Monte Carlo process is executed via the optimization summarized in Figure 21. The inner loop of this process is a traditional genetic algorithm optimization loop. Additional iterations of this inner optimization loop are performed to gain confidence in the identified solution. This is necessary due to the stochastic nature of a heuristic genetic algorithm (not provably convergent). The middle loop is used to perform the Monte Carlo analysis for a specific case. The middle loop pulls random variables from the previously identified probability

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distributions and re-executes the optimization loop while recording each candidate
solution. Finally, an outer loop enables one to perform a Monte Carlo Analysis for
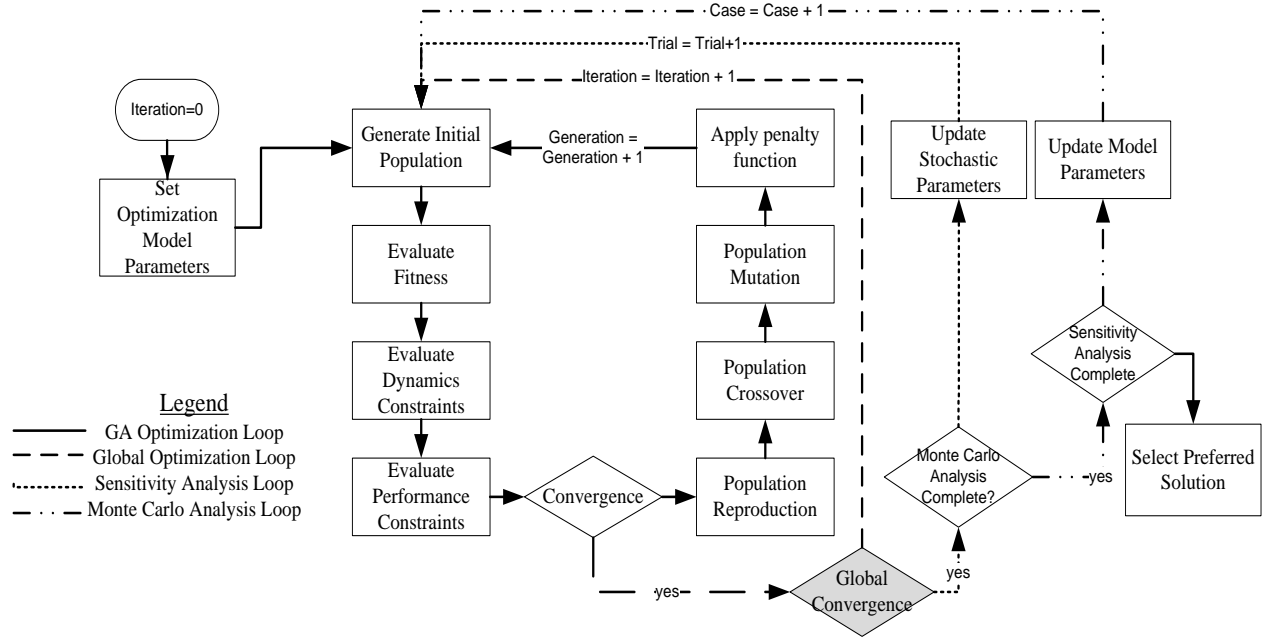varying cases (i.e. varying system requirement cases).

Figure 21. DISCO optimization process overview

Application

The aforementioned stochastic parameter methods were applied to a reference
Weather Satellite Follow-on (WSF) problem. Defense weather satellites provide
environmental data used for planning and conducting military operations worldwide [2].
Defense Meteorological Satellite Program (DMSP) satellites have been providing
weather data to the defense community since the 1960's. In 1995, a joint program
dubbed National Polar-Orbiting Operational Environmental Satellite System (NPOESS)
was established with the intent of consolidating the DoD and NOAA weather satellite
programs. The NPOESS program was cancelled in 2010 due technical and programmatic
difficulties including significant cost growth and schedule delays. In response NOAA,

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partnering with NASA, established the Joint Polar Satellite System (JPSS) and the Department of Defense established the Defense Weather Satellite System (DWSS). The DWSS concept consisted of a large multi-function satellite with a Visible Infrared Imaging Radiometer Suite (VIIRS) imaging payload, a Microwave Imager Sounder (MIS) payload, and a Space Environmental Monitoring-NPOESS (SEM-N) payload. These three payloads were all heritage NPOESS payload designs. The U.S. Congress instructed the DoD to terminate the DWSS program in 2012. The DoD has since launched its next to last DMSP satellite and is assessing options for developing the next-generation Weather System Follow-on (WSF) [3].

The WSF program is currently planned to be developed as a pathfinder disaggregated system. According to US Air Force budget documents "WSF will take a disaggregated system-of-systems approach to meet specific Department of Defense needs while leveraging near-term civilian and international partnerships" [4]. Initial WSF architecture and technology risk-reduction studies are underway. These studies are assessing visible and infrared sensor designs, microwave radiometer designs, spacecraft bus designs, and architecture alternatives [5]. This paper will apply the Disaggregated Integral System Concept Optimization (DISCO) methodology to the WSF conceptual architecture problem. The applicability of the DISCO methodology to this multi-function multi-orbit disaggregation problem was previously addressed in [**53**]. This previous application is extended in this article by assessing cost risk associated with space vehicle and launch vehicle failures.

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Stakeholder needs

Stakeholder needs were derived from the Meteorological and Oceanographic Collection (METOC) Initial Capabilities Document (ICD). The METOC ICD identified the following five space-based capability needs

1. Weather Imagery

2. Ocean Surface Wind Vector (OSWV)

3. Sea Surface Temperature

4. Soil Moisture

5. Space Environment Monitoring

The WSF mission is assumed to last 18 years from 2020 to 2038 according to information outlined in [**33**].

System Requirements

The WSF system requirements were derived by consolidating the mission needs identified in the METOC ICD with the system requirements identified in the National Polar-orbiting Operational Environmental Satellite System (NPOESS) Integrated Operational Requirements Document-II (IORD-II). The consolidated system requirements are summarized in Table 8 as previously identified in [**53**].

Table 8. WSF system requirements summary

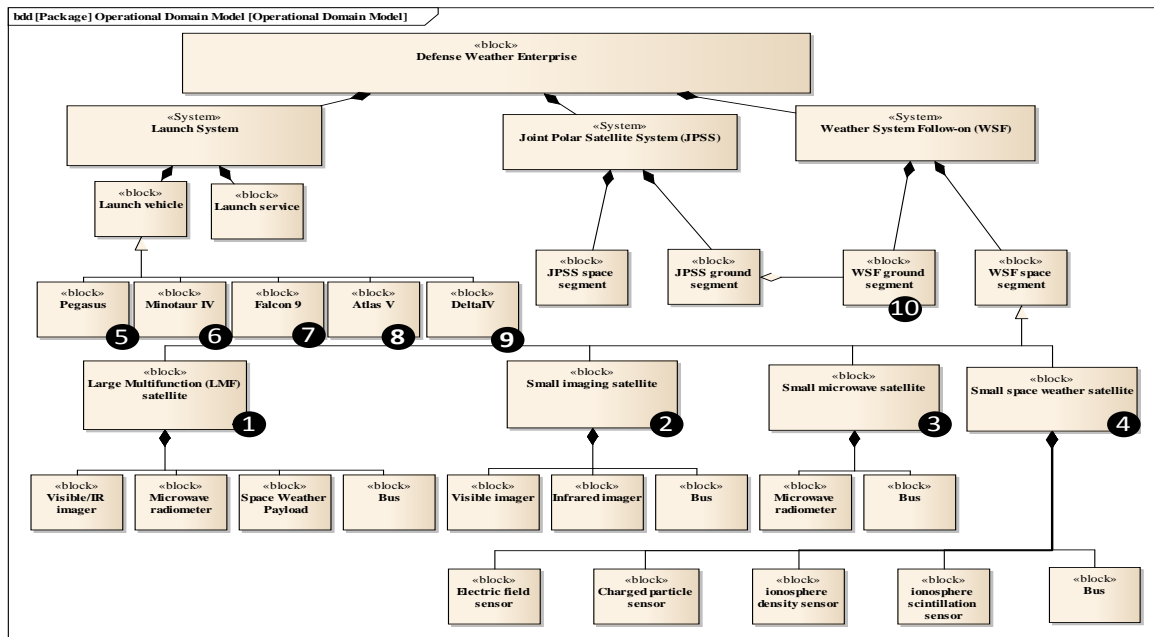|	Coverage area	Resolution	Refresh	Timeliness	Accuracy (mapping)	Accuracy (measurement)
Imagery						
Weather imagery	global	.4 km (nadir) .8 km (edge)	4 hours (avg revisit)* 6 hours (max revisit)	90 mins	1km (nadir) 3km (edge)	SNR 119 (L=22) (.64± .05µm) NEDT 2.5 (T=270K) (3.74±.38µm)
Sea Surface						
Wind speed (Clear)	global (ice-free)	20km (nadir)	6 hours	90 mins	5km	2 m/sec or 10%* NEDT .7 (305K) (19.3±.4 GHz)
Wind direction (Clear)	global (ice-free)	20km (nadir)	6 hours	90 mins	5km	20 degrees (>5m/s) NEDT .7 (305K) (19.3±.4 GHz)
Temperature (clear)	global	1 km (nadir)* 1.3 km (edge)	6 hours	90 mins	1 km (nadir) 1.3 km (edge)	uncertainty= .5 degrees C* NEDT=.396 (T=270K) (3.7±.18µm)
Temperature (all weather)	global	40 km(edge)	6 hours	90 mins	5 km	NEDT=.7 (305K) (19.3±.4 GHz)
Soil Moisture*						
Moisture content (clear)	global	1 km (nadir) 4 km (edge)	8 hours	90 mins	1 km 5 km	10% uncertainty (skin layer -.1cm) SNR 119 (L=22) (.64±.05µm)
Moisture content (cloudy)	global	40 km (nadir) 50 km (edge)	8 hours	90 mins	1 km 5 km	20% uncertainty (skin layer -.1cm)* NEDT .7 (305K) (19.3±.4 GHz)
Space Environment Monitoring						
Ionospheric density & scintillation	global	100 km	NA	90 mins		10^5 cm^{-3} or 30% .1 (amplitude),.1 radians (phase)
Charged Particles Electric field	LEO	Local	NA	90 mins	NA	15% (50 KeV to 4 MeV) 3 mV per meter (0+/- 150 mVm^{-1})

Figure 22. WSF Logical Architecture

Logical Architecture

The WSF logical architecture is summarized in Figure 22 and discussed in more detail in [65]. The WSF architecture is expected to consist of an unknown number of large multi-function spacecraft, small functionally-cohesive (small imager, small microwave, small space weather) spacecraft, the launch vehicles required to deploy these satellites, and a ground system that will operate the satellites, receive and process the mission data, and disseminate the mission data. It is assumed that the NOAA Satellite Operations Center (SOC) will continue to operate the WSF satellites as they currently operate the DMSP satellites. It is also assumed that the Air Force Weather Agency (AFWA) and Fleet Numerical Meteorological and Oceanography Center (FNMOC) will continue to process and disseminate weather data similar to the current ground system construct used for DMSP.

Optimization

The optimization formulation for the WSF problem has been updated from the previous optimization formulation summarized in [53]. The full optimization formulation with design variable bounds and constraint equations is provided in appendix A of this paper. The objective function formulation has been updated as the weighted sum of LCC and LCCR as introduced in the methodology section of this paper. The objective function LCC component is calculated according to the following equation for the 18 year mission duration[5]:

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[5] Note that the optimization objective function is a non-linear and discrete function. The estimated system cost terms $(c_i^{dev}, c_i^{prod}, c_i^{ops}, c_i^{supt}, c_i^{ret})$ are functions of the problem design variable vector ($\boldsymbol{x}$). Additionally, the system number terms $(x_i^{dev}, x_i^{prod}, x_i^{ops}, x_i^{supt}, x_i^{ret})$ are also functions of the problem design variable vector ($\boldsymbol{x}$) and can only have integer values. The $x_{i,s}$ terms are system specific design variables included in the design variable vector ($\boldsymbol{x}$).

$$LCC = C_1^{dev}x_1^{dev} + C_1^{prod}x_1^{prod} + C_1^{ops}x_1^{ops} + C_1^{sust}x_1^{sust} + C_1^{ret}x_1 + C_2^{dev}x_2^{dev} + C_2^{prod}x_2^{prod}$$
$$+ C_2^{ops}x_2^{ops} + C_1^{sust}x_2^{sust} + C_2^{ret}x_2 + C_3^{dev}x_3^{dev} + C_3^{prod}x_3^{prod} + C_3^{ops}x_3^{util}$$
$$+ C_3^{sust}x_3^{sust} + C_3^{ret}x_3 + C_4^{dev}x_4^{dev} + C_4^{prod}x_4^{prod} + C_4^{ops}x_4^{ops} + C_4^{sust}x_4^{sust} \qquad [34]$$
$$+ C_4^{ret}x_4 + C_5^{prod}x_5^{prod} + C_6^{prod}x_6^{prod} + C_7^{prod}x_7^{prod} + C_8^{prod}x_8^{prod} + C_9^{prod}x_9^{prod}$$
$$+ C_{10}^{dev}x_{10}^{dev} + C_{10}^{prod}x_{10}^{prod} + C_{10}^{ops}x_{10}^{ops} + C_{10}^{sust}x_{10}^{sust} + C_{10}^{ret}x_{10}$$
$$C_i^{dev} = C_{bus}^{dev} + C_{pl}^{dev} + C_{IA\&t}^{dev} + C_{PM}^{dev} + C_{AGE}^{dev} + C_{sw}^{dev} \text{ for } i = 1..4$$

where

$$C_i^{dev} = 0 \text{ for } i = 5..9$$
$$C_i^{dev} = 1,200,000 \text{ for } i = 10$$
$$x_i^{dev} = \begin{Bmatrix} 1 \text{ if } x_i^{prod} > 0 \\ else\ 0 \end{Bmatrix} \text{ for } i = 1..10$$
$$C_i^{prod} = C_{bus}^{prod} + C_{pl}^{prod} + C_{IA\&t}^{prod} + C_{PM}^{prod} + C_{AGE}^{prod} + C_{LOOS}^{prod} \text{ for } i = 1..4$$
$$C_i^{prod} = \{18454; 22000; 56750; 172000; 215000\} \text{ for } i = 5..9$$
$$C_i^{prod} = 0 \text{ for } i = 10$$
$$x_i^{prod} = x_{i,1} * x_{i,2} = p * s \text{ for i } = 1..4$$
$$x_i^{prod} = x_{i,1} + x_{i,2} + x_{i,3} \text{ for i } = 5..9$$
$$x_i^{prod} = 1 \text{ for } i = 10$$
$$C_i^{ops} = \frac{\left(0.035308 * (C_i^{dev})^{.928} * DL\right)^{(.03*10)}}{x_i^{ops}} + \left(.035308 * (C_i^{prod})^{0.928} * DL\right)^{(0.03*10)} \text{ for } i = 1..4$$
$$x_i^{ops} = x_i + x_i * RC \text{ for i } = 1..4$$
$$x_i^{ops} = 0 \text{ for } i = 5..10$$
$$C_i^{sust} = C_i^{prod} + SC/X_i^{sust}$$
$$x_i^{sust} = x_i + x * RC \text{ for } i = 1..4$$
$$C_i^{ret} = 1000 \text{ for } i = 1..4$$
$$C_i^{ret} = 0 \text{ for } i = 5..9$$
$$x_i^{ret} = x_i + x_i * RC \text{ for } i = 1..4$$
$$x_i^{ret} = 0 \text{ for } i = 5..9$$
$$RC = ceiling(\frac{MD}{DL} - 1)$$

LCC is the total estimated WSF system life cycle cost

C_{bus} is the estimated cost for the SV bus

C_{pl} is the estimated cost for the SV payload

$C_{IA\&T}$ is the estimated cost for SV Integration Assembly & Test (IA&T)

C_{PM} is the estimated cost for the SV program level (i.e. Program Management (PM) and Systems Engineering (SE))

C_{AGE} is the estimated cost for the SV Aerospace Ground Equipment (AGE)

C_{sw} is the estimated cost for the SV software

C_{LOOS} is the estimated cost for the SV Launch & Orbital Support (LOOS)

p is the number of satellite planes for i=1..4

s is the number satellites per plane for i=1..4

RC is the number of satellite replacement constellations

SC is the estimated storage cost (assumed to be 200,000 $K per SV type)

MD is the planned mission duration (18 years)

DL is the planned design life for each satellite type (9 years for large satellites and 6 years for small satellites based upon current commercially available spacecraft design lives for each category)

The large satellite development and production cost coefficients are calculated using the Unmanned Satellite Cost Model (USCM) and NASA Instrument Cost Model (NICM) as summarized in [**53**]. Likewise small satellite development and production cost models are estimated using the Small Satellite Cost Model (SSCM). The launch vehicle cost coefficients are based upon average historical launch vehicle costs for each launch vehicle type. The USCM, NICM, SSCM, and launch vehicle cost models are documented in chapter 11 of [**1**]. The NASA operations cost model was introduced as an improvement to the LCC equation detailed in [**53**]. The cost models are used "as is" and not examined in detail. The NASA operations cost model is detailed in [**20**] and is based upon the following CER:

$$C^{ops} = .035308 * (C_{SV})^{.928} * T$$

[35]

where
C^{ops} is the estimated yearly SV ops cost (2010 \$K)
C_{SV} is the SV cost
T is the operations time (years)

This cost estimating relationship equation is updated to 2010 dollars by using a 3% rate of inflation to maintain consistency in cost estimating year values. The operations cost model is then adapted to the DISCO optimization formulation model using the equation

$$C_i^{ops} = \frac{\left(.035308*(C_i^d)^{.928}*DL\right)^{(.03*10)}}{x_i^{ops}} + \left(.035308 * (C_i^{prod})^{.928} * DL\right)^{(.03*10)} \text{ for i} = 1..4$$

[36]

The DISCO optimization model has been appended to minimize estimated Life Cycle

Cost Risk (LCCR). LCCR is estimated according to the following equation:

$$LCCR = CR_1^{prod}x_1 + CR_1^{sust}x_1 + CR_2^{prod}x_2 + CR_2^{sust}x_2 + CR_3^{prod}x_3 + CR_3^{sust}x_3 + CR_4^{prod}x_4$$
$$+ CR_4^{sust}x_4 + CR_5^{prod}x_5 + CR_5^{sust}x_5 + CR_6^{prod}x_6 + CR_6^{sust}x_6 + CR_7^{prod}x_7 \qquad [37]$$
$$+ CR_7^{sust}x_7 + CR_8^{prod}x_8 + CR_8^{sust}x_8 + CR_9^{prod}x_9 + CR_9^{sust}x_9$$

where

$$CR_i^{prod} = P_{SVFi} * C_{SVi}^{prod} \ for \ i = 1 \ to \ 4$$
$$CR_i^{sust} = P_{SVFi} * C_{SVi}^{sust} \ for \ i = 1 \ to \ 4$$
$$CR_i^{prod} = P_{LVFi} * (C_{sv}^{prod} + C_{LV}^{prod}) \ for \ i = 5 \ to \ 9$$
$$CR_i^{sust} = P_{LVFi} * (C_{sv}^{sust} + C_{LV}^{sust}) \ for \ i = 5 \ to \ 9$$

LCC_r is the estimated WSF Life Cycle Cost Risk
CR_i^{prod} is the cost risk associated with producing replacement SVs and LVs that failed
for the initial constellation
CR_i^{sust} is the cost risk associated with producing replacement SVs and LVs that failed for
the planned sustainment (replenishment) SV constellations
P_{SVFi} is the probability of SV failure for i=1..4
P_{LVFi} is the probability of LV failure for i=5..9

The cost risk associated with on-orbit satellite failures is calculated based upon the risk of

procuring additional spacecraft to replace the spacecraft that failed prior to the end of

their design life. This probability of failure rate is calculated according to the empirical

Weibull models summarized in [**58**]. The estimated P_{SVF} is calculated according to the

following equation.

$$P_{SVF} \sim F_{SV}(t) = 1 - exp\left(-\left(\frac{t}{\theta}\right)^B\right) for \ t \geq 0 \qquad [38]$$

where
F_{sv} is the estimated failure rate for a satellite at t years
t is the number of years that an SV is on orbit
θ is the scale parameter (years)
B is the shape parameter (dimensionless

The associated failure rates for each WSF space vehicle type are then calculated as

exemplified below:

$$F_{sv,large}(9) = 1 - exp\left(-\left(\frac{9}{18215.6}\right)^{.4492}\right) = 3.4\%$$

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$$P_{SVF2} \sim F_{small} = 1 - \exp\left(-\left(\frac{6}{893150.6}\right)^{.2519}\right) = 4.9\%$$

$$P_{SVF3} \sim F_{small} = 1 - \exp\left(-\left(\frac{6}{893150.6}\right)^{.2519}\right) = 4.9\%$$

$$P_{SVF4} \sim F_{small} = 1 - \exp\left(-\left(\frac{6}{893150.6}\right)^{.2519}\right) = 4.9\%$$

The large SVs have a slightly lower estimated failure rate, however it is not substantially less than the empirically estimated failure rates for small SVs. This is somewhat surprising considering that historically small satellites have single string designs to reduce mass.

The launch vehicle failures rates were then calculated according to the Bayesian failure rate estimation equation detailed in [60] and discussed in the methodology section for the potential WSF launch vehicle types. As the WSF program is a U.S. DoD mission, the launch vehicles were limited to current U.S. domestic launch vehicles according to the National Space Transportation Policy. The number of launch vehicle successes and failures were determined from the 2013 Space Launch Report [66]. The launch vehicle reliabilities were then calculated as exemplified below:

$$P_{LVF5} \sim F_{Pegasus\ XL} = 1 - \frac{37 + 1}{42 + 2} = 13.6\%$$

$$P_{LVF6} \sim F_{Minotaur\ IV} = 1 - \frac{4 + 1}{4 + 2} = 17\%$$

$$P_{LVF7} \sim F_{Falcon9} = 1 - \frac{2 + 1}{2 + 2} = 25\%$$

$$P_{LVF8} \sim F_{Atlas\ V} = 1 - \frac{41 + 1}{42 + 2} = 5\%$$

$$P_{LVF7} \sim F_{Delta\ IVH} = 1 - \frac{6 + 1}{7 + 2} = 22\%$$

These LV failure rates can be viewed as conservative estimates of the current failure rates given that they were extrapolated from data through 2013 and each of these launch vehicles have had many successful launches in 2014 and several vehicles such as the Falcon 9 were relatively new in 2013. Therefore it should be expected that the overall

reliability of these systems will trend upward towards the 90-95% historical reliability ratings as these launch vehicles fulfill their planned manifests.

Applied Monte Carlo Analysis

The four step Monte Carlo analysis procedure, discussed in the methods section of this paper, was applied to the WSF conceptual design optimization problem. First, the system logic was established by modeling the WSF problem according to the DISCO optimization model where optimal solutions are defined as the minimum weighted cost solution (i.e. Min $f(x, p) = \omega_1 LCC + \omega_2 LCCR$ where $\omega_1 = 1$ and $\omega_2 = 1$). Secondly, the failure rate probability distributions were modeled for the probabilistic LV and SV failure rates. Launch vehicle failure rate distributions were modeled according to the Bayesian analysis techniques summarized in [**60**] updated with empirical data from [**66**]. The resulting LV failure rate distributions for the five possible launch vehicles selected for the WSF problem are summarized in Figure 23.
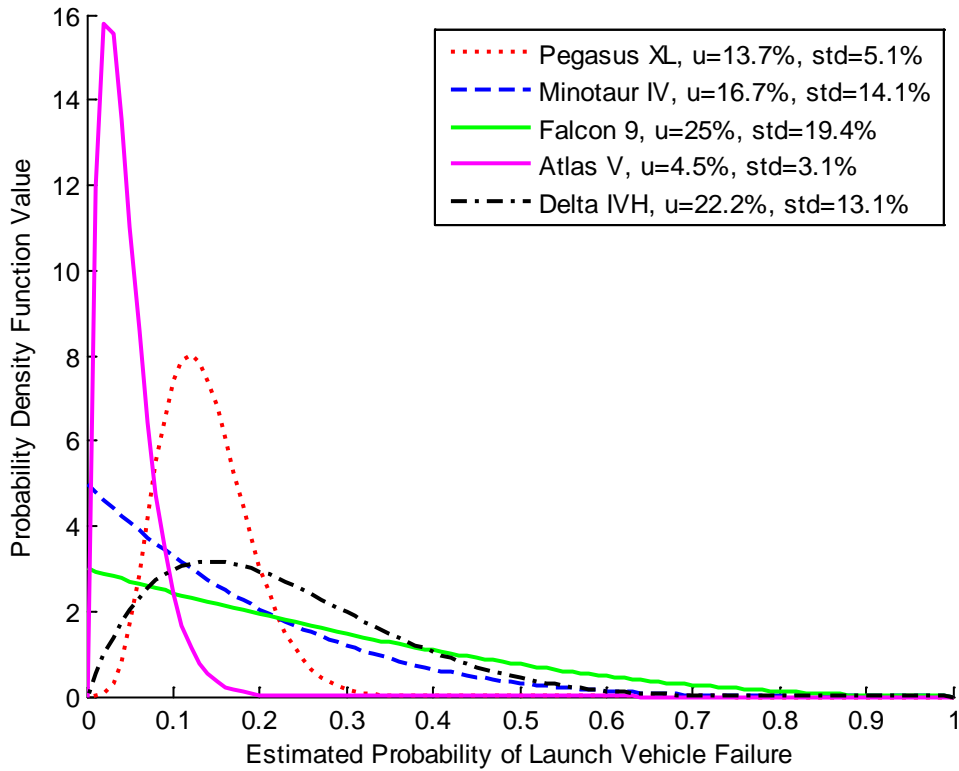
Figure 23. Probability density function for WSF associated launch vehicle failures.

Space Vehicle failure rate distributions were modeled as a normal distributions based upon the techniques and empirical data summarized in [**58**]. The resulting distribution for the large and small WSF satellite types with respective 9 and 6 year design lives are summarized in Figure 24. Third, Random failure rates were sampled from these distributions and input into the optimization formulation for each Monte Carlo trial. The optimization routine was then executed with 10 global optimization iterations and 100 Monte Carlo trials. The results from the optimization were recorded and a normalized histogram is developed. The normalized histogram provides an approximation of the resulting PDF. A Gaussian mixture distribution was fit to the results and the resulting mixed Gaussian distributions were used to produce PDF and

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CDF summaries for the results. The resulting PDF and CDF summaries for the threshold WSF problem are shown in Figure 25. Finally, the Monte Carlo procedure was executed for multiple cases via the outer sensitivity analysis loop shown in Figure 21. For each case the constraints associated with a system requirement was varied. The Key Performance Parameter requirement associated with all-weather Microwave Ocean Surface Wind Vector (OSWV) revisit rate was varied from 8 hours (threshold requirement minus 2 hours) to 1 hour (objective requirement). The weighted cost trade study curve, PDF, and CDF results are assessed and summarized in the subsequent results section of this article.
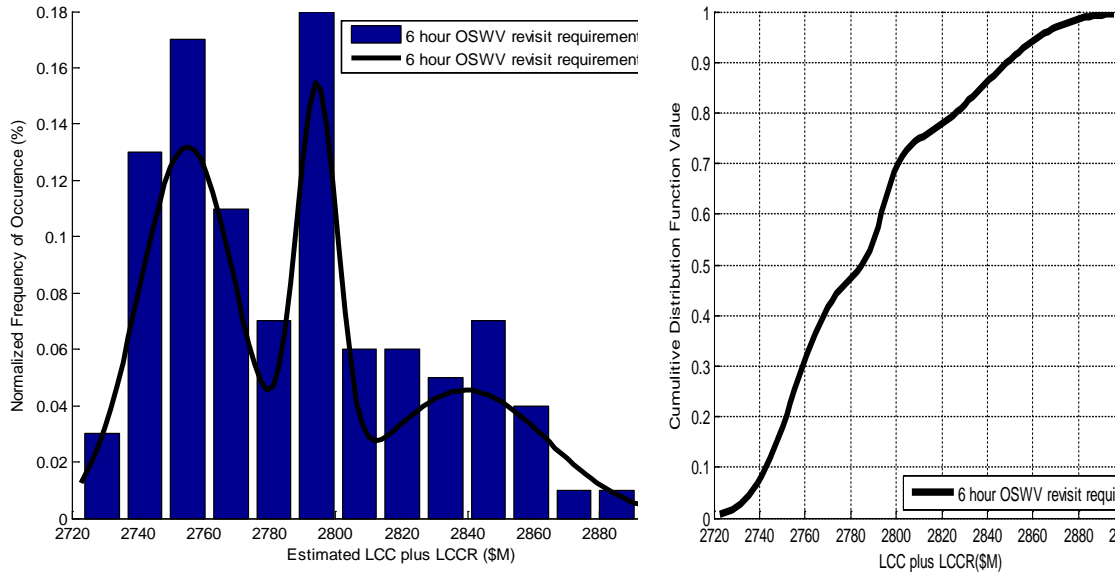

Figure 24. Probability density function for large and small WSF space vehicles failures.
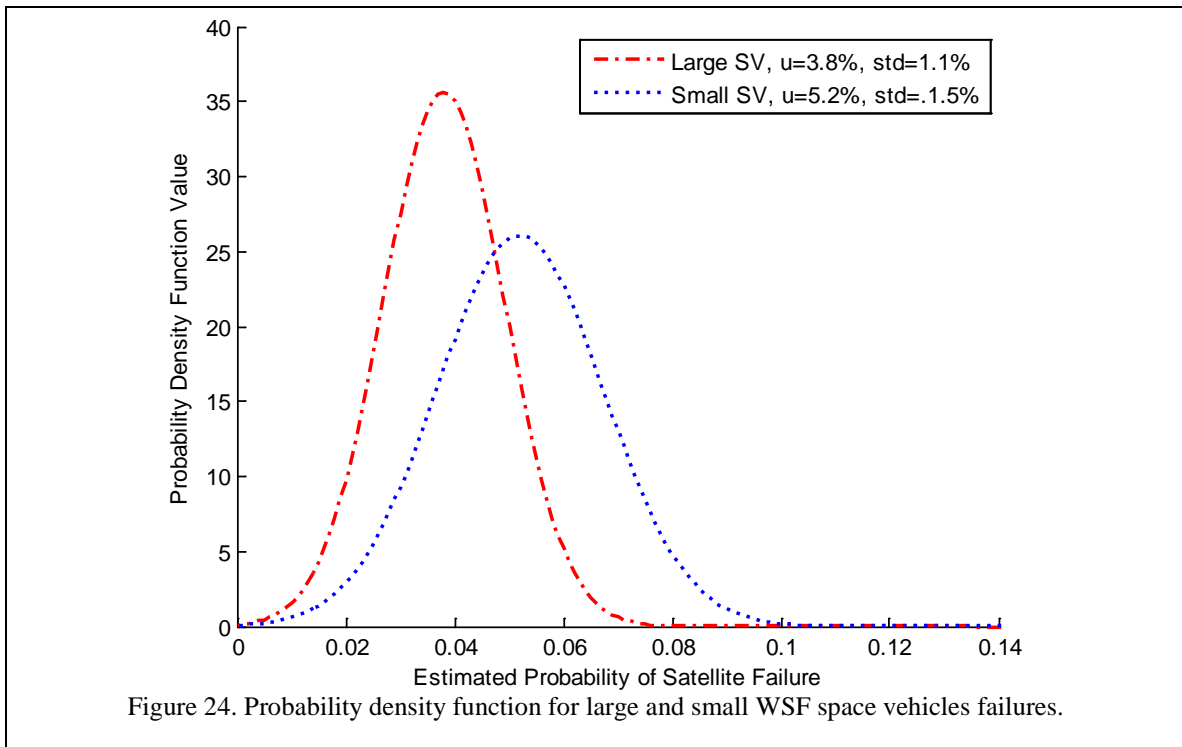
Figure 25. Estimated PDF (left) and CDF (right) functions for WSF threshold requirements case

WSF results assessment

The optimization routine was executed 10 times for each trial according to the optimization process outlined in [**53**]. The architecture solution was then recorded and the best solution for each scenario is presented in the results section. An initial analysis was completed to determine whether a higher launch vehicle and space vehicle failure rate would change the near-optimal architectural solution identified. The impacts of various satellite failure rates were assessed by significantly increasing the estimated satellite failure rate. The impacts of various launch vehicle failure rates were assessed in the same manner. Finally, a Monte Carlo analysis was conducted and the corresponding outputs are discussing in the subsequent sections of this paper.

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Results

WSF Results

The identified minimum cost solution, referred to as Disaggregated Weather System Follow-on (DWSF), is summarized and compared to the baseline Defense Weather Satellite System (DWSS) concept in Table 9. The DWSS concept preceded the WSF program. The DWSS SV contained a Visible Infrared Imager Radiometer Suite (VIIRS) payload, a Microwave Imager/Sounder (MIS) payload, and a Space Environment Monitor-NPOESS (SEM-N) payload integrated on single large multi-function satellite bus. The DWSS concept and associated cost estimate basis is outlined in [**33**].

Table 9- DWSF minimum LCC solution compared to DWSS baseline

	DWSS	DWSF
#SV type 1 (large)	2 (2/1)	0
#SV type 2 (imager)	0	2 (2/1)
#SV type 3(microwave)	0	8 (2/4)
#SV type 4 (space weather)	0	4 (4/1)
#LV type 5 (Pegasus)	0	2
#LV type 6 (Minotaur)	0	2
#LV type 8 (Atlas V)	2	0
Estimated LCC	$8282M	$2717M
Estimated LCCR	$205M	$88M

The result of the DISCO method applied to the WSF mission requirements in Table 9 identifies an estimated $5.57 Billion in estimated life cycle cost savings and an estimated $5.68 Billion in risk weighted cost savings. This represents a significant margin of improvement garnered through disaggregation and optimization. Further analysis was then conducted on variations to the DWSF solution derived from changes in stochastic LV and SV reliability values. Initial results indicate that the minimum estimated cost (LCC) solution is also the minimum estimated cost risk (LCCR) solution for the

empirically derived LV and SV failure rates. A summary of the optimization results demonstrating this relationship is provided in Table 10. The architecture for the lowest estimated cost solution was also the lowest cost risk solution based upon an equal weighting. The estimated LCC is $2717M. The estimated life cycle cost risk associated with this solution is $88M.

Table 10- Optimization results summary for weighted LCC and LCCR architectures

	Minimize LCC ($\omega_1=1$) ($\omega_2=0$)	Minimize LCCR ($\omega_1=0$)($\omega_2=1$)	Minimize LCC+LCCR ($\omega_1=1$) ($\omega_2=1$)
#SV type 1 (large)	0	0	0
#SV type 2 (imager)	2 (2/1)	2 (2/1)	2 (2/1)
#SV type 3(microwave)	8 (2/4)	8 (2/4)	8 (2/4)
#SV type 4 (space weather)	4	4	4
#LV type 5 (Pegasus)	2	2	2
#LV type 6 (Minotaur)	2	2	2
Estimated LCC	$2717M	$2717M	$2717M
Estimated LCCR	$88M	$88M	$88M
Weighted function	$2717M	$88M	$2805M

The small launch vehicles (Pegasus XL and Minotaur IV) identified in the near optimal solution are statistically less reliable than the large launch vehicles however the reduced cost risk associated with the less likely failure of these launch vehicles are not large enough to outweigh the increased cost of using larger launch vehicles. A simple analysis was conducted to determine whether a significantly less reliable small launch vehicle would impact the conceptual architecture solution. The failure rate of the Pegasus XL was increased from the empirically estimated 13.7% at even 10% increments to 40%, at which point the minimal cost risk and risk weighted cost solutions change. The corresponding results of this analysis are summarized in Table 11. The minimum estimated cost solution remains the same as the previously identified best solution. The minimum cost risk and weighted cost risk solutions allocate the small imager satellites to

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a Minotaur IV launch vehicle to address the high failure rate of the Pegasus XL launch vehicle. All other aspects of the architectural solution remain unchanged.

Table 11. Optimization results summary for weighted LCC and LCCR architectures based upon empirical SV failure rates with adjusted Pegasus reliability (40%)

	Minimize LCC (ω_1=1) (ω_2=0)	Minimize LCCR (ω_1=0) (ω_2=1)	Minimize LCC+LCCR (ω_1=1) (ω_2=1)
#SV type 1 (large)	0	0	0
#SV type 2 (imager)	2 (2/1)	2 (2/1)	2 (2/1)
#SV type 3 (microwave)	8 (2/4)	8 (2/4)	8 (2/4)
#SV type 4 (space weather)	4	4	4
#LV type 5 (Pegasus)	2	0	0
#LV type 6 (Minotaur)	2	4	4
Estimated LCC	$2717M	$2738M	$2738M
Estimated LCCR	$88M	$96M	$96M
Weighted function	$2717M	$96M	$2834M

As an aside, the availability of the Pegasus launch vehicle for DoD missions is uncertain. The optimization routine was executed without the Pegasus as an available launch vehicle type and the results matched the updated solution identified in columns 2 and 3 of Table 11. Similar to the high failure rate Pegasus XL case, the architecture changed minimally by allocating the small imager satellites to Minotaur LVs with an increase to LCC of approximately $21M and an increase to LCCR of approximately $8M.

An analysis was then conducted to determine the impact of a significant degradation in space vehicle reliability. The small space vehicle failure rate was increased from the empirically modeled 5.2% in even 10% increments until the minimum risk solution changed at 50%. The results of this analysis are summarized in Table 12. Significant architecture changes only occurred for the minimum risk solution. This solution reduces the number of small microwave satellites from 8 to 7, each SV placed

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into a separate orbital plane by a single Pegasus XL launch vehicle. Consequently the

cost risk associated with satellite failures is reduced according to the reduced number and

estimated cost of microwave satellites. However, this increases the overall estimated life

cycle cost of the solution by increasing the number of Pegasus XL launch vehicles

required to launch the microwave satellite constellation. Consequently, the minimum

balanced cost and cost risk solution is consistent with the minimum cost solution

identified previously. This result indicates that the identified minimum cost solution is

robust to significant decreases in space vehicle reliability.

Table 12. Optimization results summary for adjusted small SV failure rate (50%)

	Minimize LCC (ω_1=1) (ω_2=0)	Minimize LCCR (ω_1=0) (ω_2=1)	Minimize LCC+LCCR (ω_1=1) (ω_2=1)
#SV type 1 (large)	0	0	0
#SV type 2 (imager)	2 (2/1)	2 (2/1)	2 (2/1)
#SV type 3 (microwave)	8 (2/4)	7 (7/1)	8 (2/4)
#SV type 4 (space weather)	4	9	4
#LV type 5 (Pegasus)	2	9	2
#LV type 6 (Minotaur)	2	0	2
Estimated LCC	$2717M	$2961M	$2717M
Estimated LCCR	$218M	$203M	$218M
Weighted function	$2717M	$203M	$2936M

It is important to note that none of the identified solutions included large multi-function

satellites. The increased estimated development, production, and launch vehicle costs

associated with large satellites results in architectures led to significantly larger cost and

cost risk solutions despite longer assumed design lives and higher estimated individual

satellite reliability. This result remains even after the small space vehicle reliabilities

were reduced to 50% (which has less than a 5% likelihood according to the empirical SV

failure rate data) while the large space vehicle reliability was maintained at 96.6%.

The results from this analysis can be used to inform programmatic decisions with

regards to overall system reliability. For example, if a single small microwave satellite

fails in the DWSF solution there is minimal capability loss. The capabilities associated with the imagery SV and space weather SV are still intact and the revisit rate for the products associated with the microwave SV are only minimally reduced. A single large satellite loss would have significant impact, by comparison, on the capability of the system by significantly reducing the revisit time for all mission data products. Additionally, the magnitude of cost risk can inform decisions regarding reconstitution and replenishment. The life cycle cost risk associated with LV and SV failures for the DWSS concept is estimated at $205M. The estimated production cost of a DWSS satellite is $864M. Consequently, it is difficult to justify the procurement of an additional DWSS SV for rapid replenishment of the constellation after a failure. Alternatively, the life cycle cost risk associated with LV and SV failures for the DWSF solution is estimated at $77M. The combined production costs for a single small imager, small microwave, and small space weather SV is approximately $72M. Consequently, production of ground or on-orbit spares for the DWSF constellation is comparatively easy to justify.

WSF Monte Carlo Results

WSF Monte Carlo analysis results are summarized in Figure 26.   All of the solutions consist of small imager, small microwave, and small SEM satellites. All of the solutions consist of 2 small imager satellites deployed individually into 2 planes by a Pegasus XL launch vehicle. The number of small microwave satellites increases exponentially as the Ocean Surface Wind Vector (OSWV) revisit requirement is tightened from 8 hours (threshold requirement minus 2 hours) to the objective value of 1 hour. The number of small SEM satellites increase incrementally as the number of small

microwave satellites increase. This incremental increase was expected as the local space weather requirements were modeled such that each satellite plane should include a SEM payload or small SEM satellite.
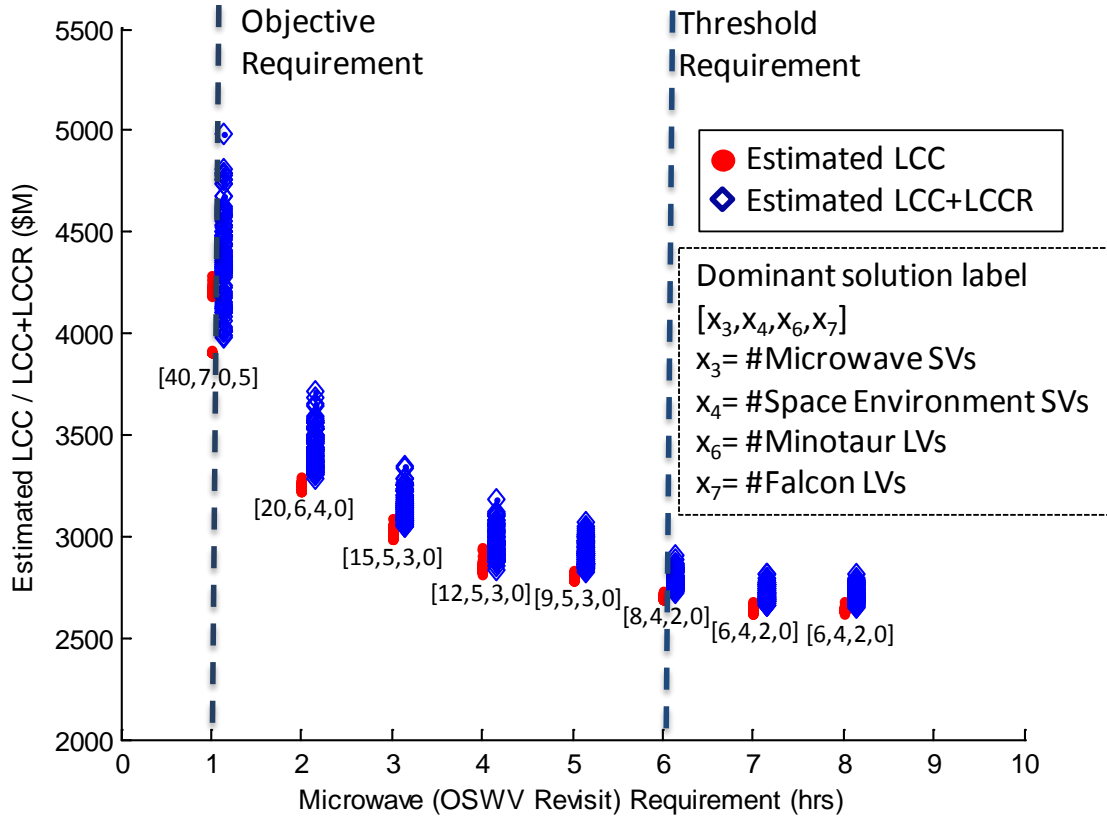

Figure 26. Monte Carlo Analysis results summary

The estimated WSF LCC values increase exponentially as the number of small microwave satellites increase exponentially. The variation in risk weighted cost (LCC plus LCCR) values also increases exponentially as the number of microwave satellites increase.

The number and type of launch vehicles vary among solutions depending upon the randomly selected launch vehicle failure rate values. The majority of solutions, for

the 8 hour to 2 hour OSWV requirement cases, consist of Minotaur 4 LVs that are allocated to clustered planes of 2, 3, 4, or 5 Microwave SVs. Approximately, 70-80 percent of the solutions consist of Minotaur IV launch vehicles assigned to the small microwave and SEM SVs. Approximately 20-30 percent of the solutions consist of Falcon 9 LVs allocated to the microwave and SEM SVs. The min risk weighted cost solutions contain Falcon 9 LVs only when the randomly sampled Minotaur IV failure rate is significantly greater than the randomly sampled Falcon 9 LV failure rate. The corresponding reduction in LCCR of the Falcon 9 solution must be large enough to outweigh the increased production cost of the Falcon 9 vs. the Minotaur 4. The results for the 1 hour OSWV revisit requirement case are substantially different than the other cases. The majority (61%) of solutions for the 1 hour case consist of 5 planes of 8 microwave satellites launched on 5 corresponding Falcon 9 LVs. The remaining cases (39%) consisted of 8 planes of 5 microwave satellites launched on 8 corresponding Minotaur IV LVs. This result appears to be related to a change in constraint boundaries. The large number of microwave SVs required to meet the 1 revisit requirement favors a launch vehicle with the ability to launch larger clusters of satellites. However, the Falcon 9 LV has a relatively large failure rate distribution enabling multiple Minotaur IV based solutions with a higher estimated LCC but lower LCC plus LCCR value.

The Monte Carlo PDF results are summarized in Figure 27 for selected cases (6 hour-threshold, 3 hour, and 1 hour-objective). The general shape of the 5, 4, and 2 hour cases were similar to the 1 and 3 hour case and were excluded for figure readability. These PDF results indicate that the minimum risk weighted cost (LCC plus LCCR) values for optimized solutions tend to be skewed right and multi-modal. The PDF peaks

correlate with the empirically estimated min risk weighted cost solutions.   The multi-modal nature of the PDF results appears to be caused by the combination of underlying distributions associated with the mixed launch vehicle solution sets.   For example, the multi-modal shape of the output pdfs shown in Figure 27 appear to be primarily scaled results of the summed Minotaur 4 and Falcon 9 launch vehicle failure rate distributions shown in Figure 23.
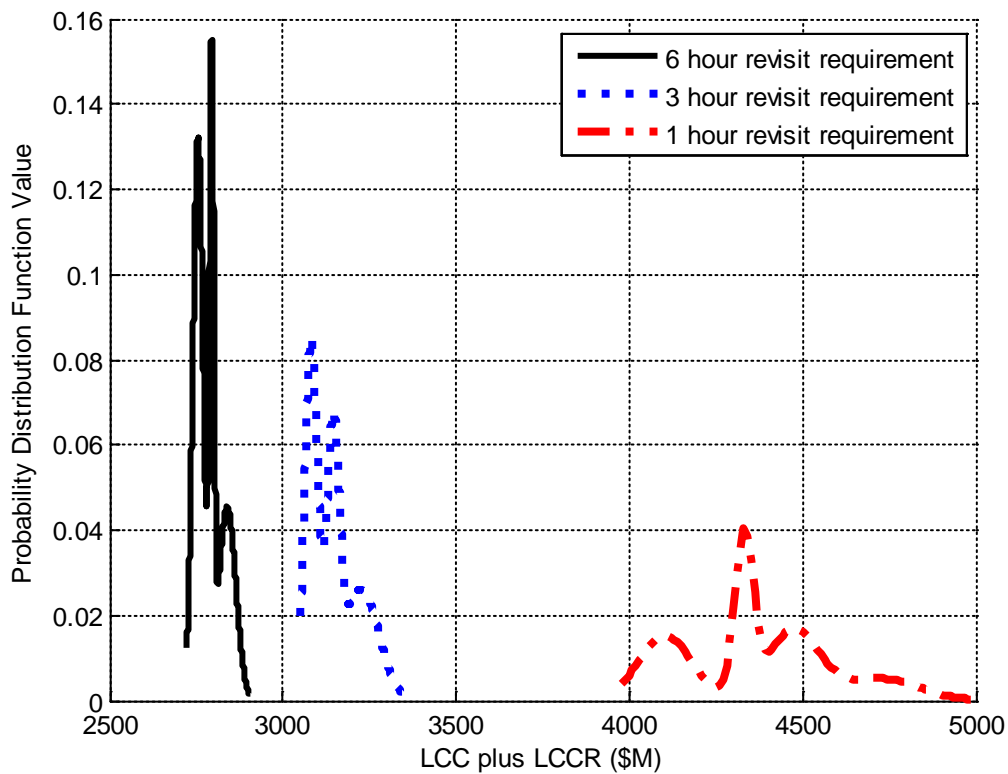

Figure 27. Monte Carlo Probability Density Function summary for the WSF trade study cases.

The Monte Carlo CDF results are summarized in Figure 28. These CDF results provide critical information for the system architect or acquisition decision maker. These results can be used to associate program risk weighted cost with a given confidence level

when stochastic LV and SV failure rates are included in the assessment. For example,

the system architect has 80% confidence that overall cost for the WSF program

(threshold 6 hour OSWV requirement case) will not exceed $2,820M when recovery

costs associated for catastrophic LV or SV failures are accounted for. Likewise, if a

WSF program constraint existed that stated the maximum life cycle cost should not

exceed $3,000M then multiple solutions could be selected. With this $3,000M constraint

one could choose the conceptual design associated with a 4 hour OSWV revisit

requirement with 70% confidence. Alternatively, the 5 hour and 6 hour conceptual

design solution would be associated with an 80% and greater than 95% confidence
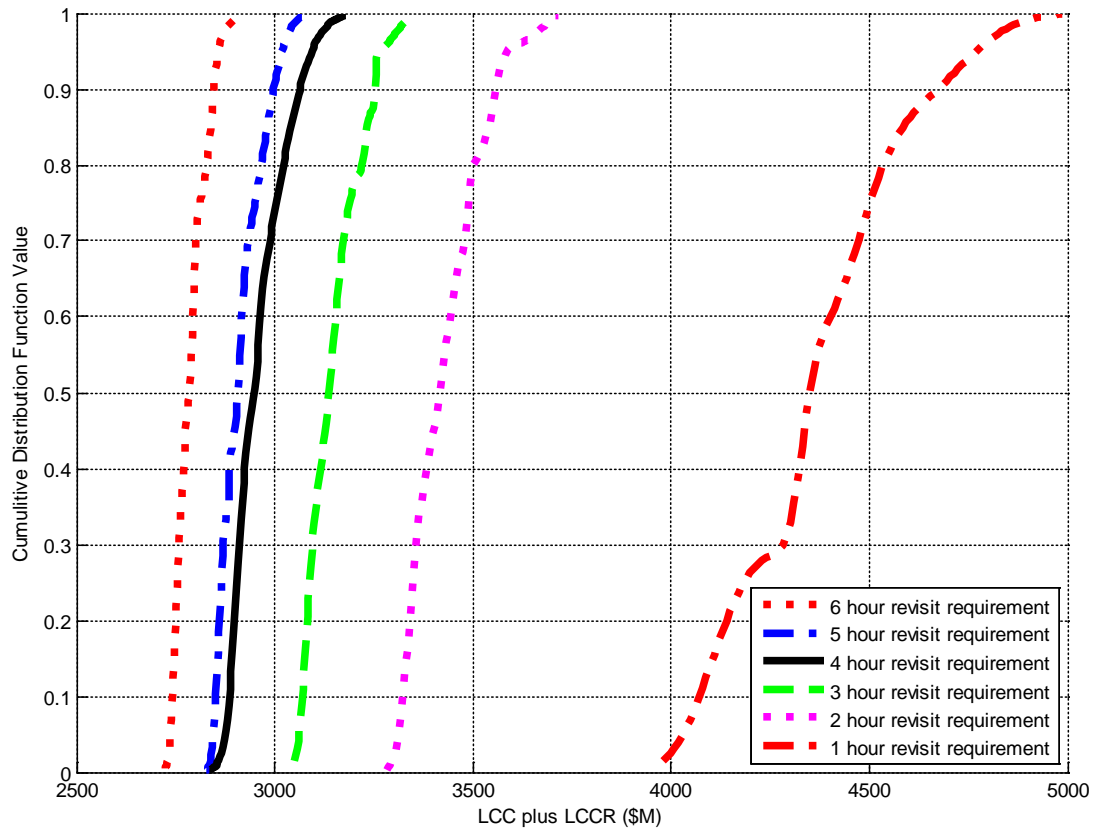
respectively.

Figure 28. Monte Carlo Cumulitive Density Function summary for the WSF trade study cases.

Summary

It has been stated that space system "disaggregation lowers the cost of individual vehicles and the operational impact of losing a vehicle. This approach allows more tailored mission assurance and smaller launch vehicles, which reduces the cost of launch" [**3**]. The DISCO methodology has been proposed as an extensible methodology to quantitatively assess whether disaggregation lowers system life cycle costs (vs. individual vehicle costs), reduces impacts of failures, and ultimately enables more tailored mission assurance solutions. To this end, this paper has introduced stochastic (empirical

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probability and Monte Carlo) methods that enable the assessment of the complex cost vs. risk design space.   The DISCO methodology proved to be extensible to incorporating stochastic failure rate analysis. Launch vehicle and satellite failure rate impacts were modeled as cost risk. The inclusion of satellite cost risk only required changes to the objective function and direct calculation of satellite failure cost risk associated with the production of a replacement satellite. The optimization formulation required a modification to assess risk associated with launch vehicle failures identified for each satellite constellation. Application analysis identified estimated life cycle cost savings upwards of five billion dollars when compared with the alternative DWSS concept. The results of this paper indicates that the optimized Disaggregated Weather System Follow-on (DWSF) solution is also the minimal cost risk solution when empirically derived stochastic space vehicle and launch vehicle failure rates are accounted for as cost risk. The results of this paper also indicate that disaggregated satellite constellations may in fact lower system life cycle costs, reduce the cost and operational impact of losing vehicles, and enable more tailored mission assurance and smaller less costly launch vehicles.   Additional resiliency advantages such as smaller operational impact of lost vehicles, placement of satellites in less congested environments, and reduced benefit vs. cost of hostile acts are inherent to the identified disaggregated solutions identified for the WSF problem. Further extensions to this approach are planned such as the inclusion of development cost risk and improved ground system modeling.

V. Conclusions and Recommendations

This chapter summarizes conclusions from the individual chapters, identifying the significance of the individual contributions in context, identifying recommended actions derived from the research process, and recommending future research.

Conclusions of Research

Conclusions related to this research fall into the following three general categories; conclusions related to the objectives, answers to the research questions, and answers to the research hypotheses. Overall it was concluded that the DISCO methodology represents an evolutionary improvement in disaggregated space system conceptual design. Solving heterogeneous space system problems using a constrained Mixed Variable Optimization formulation enables the automated generation and evaluation of a vast number of alternative architecture concepts in a much more efficient manner than the current manual approaches. The integration of a model based reference architecture and the optimization formulation enables the efficient documentation of alternative concepts and trades associated with alternative concepts. This reference architecture forms a strong basis for model refinement throughout the system life cycle.

Four conclusions were ascertained as generalized answers to the research questions. Research question #1 was: How does one model/optimize disaggregated space system concepts? Model Based Systems Engineering (MBSE) and Mixed Variable Optimization (MV-OPT) methods were identified as effective methods for modeling/optimizing disaggregated space system concepts. The DISCO methodology extended these extant methods by introducing methods that model heterogeneous system

types as design variables in the MV-OPT construct and modeling system requirements and model parameters as optimization constraints. Research question #2 was: How does one model/optimize multi-orbit/multi-function disaggregated space system concepts? Functional/physical allocation methods derived from the Object Oriented System Engineering Method were identified as capable methods for modeling multi-function disaggregated space systems. The DISCO methodology extended the OOSEM process by creating a method for mapping these allocations to an MV-OPT formulation. Research question #3 was: How does one conduct trades studies and requirements sensitivity analysis for disaggregated space system concepts? Iterative optimization and sensitivity analysis methods proved effective for identifying the impact of requirements or parameter trades on concept life cycle cost and life cycle cost risk. Research question #4 was: How does one assess the impact of stochastic variables on disaggregated space system architectures? Risk modeling and Monte Carlo simulations were concluded to be effective for determining the impact of stochastic variables on optimal concept designs.

Four general conclusions were ascertained as answers to the research hypotheses identified in Chapter I. First, it was hypothesized that heterogeneous systems would be identified as near optimal solutions for multi-orbit disaggregation problems. Results indicate that this hypothesis was incorrect and solutions tend towards homogeneous satellite constellations for multi-orbit disaggregation problems such as the example fire detection problem. Secondly, it was hypothesized that heterogeneous satellite constellations would be identified as near optimal solutions for multi-function/multi-orbit disaggregation problems. Results indicate that this hypothesis was correct and these heterogeneous constellations demonstrate significant cost improvements for complex

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multi-orbit multi-function problems such as the example defense weather system follow-on concept. Third, it was hypothesized that optimal disaggregated systems would have lower system cost risks due to failure than concepts based upon large aggregate space vehicles. Results indicate that this hypothesis was correct for the WSF problem and is likely correct other multi-orbit multi-function disaggregated space system problems.

Overall it was concluded that DISCO is an effective and extensible methodology for optimizing disaggregated space system architectures. Research developing and applying the DISCO methodology also led to a number of significant and original contributions.

Significance of Research

The significance of the research is two-fold. First the research is significant as it represents an evolutionary improvement in space system conceptual design methods. Secondly, this research is significant as it relates to the specific design results ascertained through the newly developed methodology.

Significant and original methodology contributions are made related to disaggregated space system modeling, optimization formulation, orbital performance estimation, requirement based optimization constraint methods, and stochastic analysis/risk optimization. Methods for modeling the various disaggregation concepts in a systems architecture framework are newly-developed for this research. A heterogeneous system optimization formulation is original and is significant as it enables generation and assessment of concepts for various disaggregation strategies. An original formulation for accurately approximating the average revisit of heterogeneous Walker-

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delta constellations analytically was also developed in the course of this research. The disaggregated space system optimization formulation that correlates system requirements with optimization constraints is perhaps the most significant methodology improvement. A system requirement constrained optimization formulation significantly improves the linkage between space system optimization and the top-down requirements driven systems engineering process. This system requirement constrained optimization formulation also significantly improves the ability of the architect to determine the cost and risk impacts associated with varying system requirements. The newly introduced stochastic analysis methods significantly improve the architect's ability to assess cost/ cost risk impacts in real-world scenarios where design parameters, such as the probability of system failure, are inherently random.

The novel conceptual designs resulting from the application of the newly developed methods are also significant. Conceptual design results identified in Chapters II-IV represent promising solutions to pressing needs (space-based fire detection and weather systems). These results model significant cost and risk reduction opportunities for future systems. These results also indicate that similar cost and risk improvements are likely to be identified by applying the DISCO methodology to other space system applications such as imagery, global navigation, missile warning, missile defense, and/or space surveillance.

Improved space system conceptual design methods and results may also lead to larger impacts related to the overall system acquisition enterprise. Cost effectiveness gains related to space systems would help close budget gaps in a fiscally constrained

environment. Alternatively, cost savings could be applied to other system modernization efforts or the initiation of new system developments.

Recommendations for Action

Recommendations for action resulting from this research include integrating the identified research methods into space system engineering curriculum and texts, improving optimization and system architecture tools, and communicating the methods and results to the greater system acquisition community.

It is recommended that the systems engineering educational community consider adoption of the summarized methodology into systems engineering and space system educational frameworks. Specifically, AFIT should considering introducing the DISCO methodology in the Space Mission Analysis and Systems Design course (ASYS 531), System architecting (SENG 640), and the Advanced Topics in Systems Architecture (SENG 740) courses. Introducing the methods discussed in this research could improve students' capability to effectively architect solutions complex system architecture problems. It is also recommended to develop an Appendix to the Space Mission Engineering textbook [**1**].   It is envisioned this appendix would apply the DISCO methodology to the Firesat example provided in the text similar to chapter II. Inclusion of this research would expand the current space mission engineering body of knowledge and expand current methods focused on techniques for identifying and analyzing point design concepts.

Two primary recommendations for future action were identified related to systems engineering tools. First, a genetic algorithm optimization function should be

developed that is capable of constrained multi-variable optimization where the constraints are allowed to be non-linear constraint functions. The sensitivity analysis methods discussed in Chapter III and the Monte Carlo techniques discussed in Chapter IV implemented iterative single objective optimizations for each requirements case. This analysis would likely be significantly more computationally efficient if a multi-objective genetic algorithm could be used. However, this would require a multi-objective genetic algorithm that allows non-linear constraint functions and none of the publically available genetic algorithms surveyed allow this. Secondly, system architecture tool developers should continue to improve the integration between systems engineering descriptive models and analytical engineering analysis tools. System architecture plug-ins, such as Paramagic® and MBSE Pak®, have greatly improved this integrated capability. However, it is still difficult to develop and troubleshoot integrated descriptive/analytical models. Improvements to the SysML specification or the development of software wizards that guide users through the steps discussed in Appendix B would improve a system architect or modeler's capability to develop executable models with concordance.

It is recommended that the results of this research be communicated with the larger acquisition community. Continued communication with the Weather System Follow program office is likely to aid the WSF system architecture development process. A strategic overview of this research should also be developed for publication in a forum intended for presentation of innovative thinking on military doctrine such as the Air & Space Power Journal.

Recommendations for Future Research

Several recommendations for future research were identified through the course of this research effort. Recommendations for future research relate to value modeling, ground system and software modeling, hosted payloads, expanded risk components, subsystem performance verification, and additional space system mission applications.

The inclusion of value modeling into the DISCO methodology is a promising area for future research. A proposed method for incorporating value modeling into the DISCO methodology is based upon multi-attribute value analysis techniques described in [**40**] as a "quantitative method for aggregating stakeholder's preferences over conflicting objectives to find the alternative with the highest value when all objectives are considered." It is envisioned that this value model would enable the selection of alternative optimal solutions identified through the sensitivity analysis methods discussed in chapter II. The proposed objectives would map to the various components of cost, performance, and risk.

Another promising area for future research relates to expansion of the ground system and software models. It is recommended that the ground system model be updated to enable the optimization of alternative ground system architectures. The ground system model would enable the system verification of critical system requirements that span the ground and space system such as data latency. A ground system model is also envisioned to enable the optimization of ground terminal type, number, and location. Improvements to the software model would likewise increase the fidelity of the overall model. Envisioned improvements include accounting for separate mission payload

software functionalities and the increasing complexity factors of integrating these software functionalities.

Future research expanding the DISCO methodology to include hosted payload disaggregation is recommended. It is envisioned that hosted payloads would be included in the reference architecture and optimization formulation as specialized system types. The hosted payload parameters would be constrained by the potential host spacecraft parameters. For example the Iridium Next constellation has published set mass, power, and volume constraints for potential hosted payloads. Additionally, design variables such as the orbital altitude would also be fixed by the host spacecraft constellation design. The inclusion of hosted payload system types in the DISCO methodology may enable more cost effective and lower risk concept designs.

Future research expanding the DISCO methodology to include Multi-domain disaggregation methods is recommended. The space situational awareness mission is a good example on an application that would benefit from the extension of the DISCO methodology to multi-domain disaggregation. The space situational awareness mission currently consists of radar and electro-optical sensors in the ground domain and electro-optical sensors in the space domain. The DISCO method should be extended to enable the automated generation, assessment and optimization of a space situational awareness system concept that contains the optimal configuration of space-based systems and ground-based systems.

Future research should be conducted on incorporating additional cost risk components into the methodology. The Monte Carlo risk analysis formulation should be improved by incorporating space vehicle development and production cost risk. Space

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vehicle development and production cost risk should be introduced as random variables based upon the cost component standard estimated error provided for each of the cost models used. Launch vehicle production cost risk should also be included based upon empirical data. Inclusion of cost risk associated with other potential causes for space vehicle failure such as orbital debris would also improve the fidelity of the model.

Future research should be conducted on expansion of the modeling methods for expanded requirements trades and verification. Constraints could be included to verify subsystem requirements such as estimated power collected is sufficient to meet operational duty cycle requirements. Constraints could also be incorporated verifying adequate data link and data storage capacity. Additionally, the modeling methods could be extended to enable the simultaneous variation of multiple constraint requirements. These extended methods would likely require further research into improved computational efficiency such as the use of massively parallel computing platforms such as distributed computing systems or supercomputers.

Finally, research should be conducted applying the DISCO methodology to other space system missions and possibly non-space missions such as missions related to remotely piloted aircraft. For example, the application of the DISCO methodology to the missile warning, missile defense, military communications, and space situational awareness (described above) mission are likely to identify cost effective concept designs enabling significant savings across the AFSPC space system acquisition portfolio. Likewise, the DISCO methodology could be used to identify cost effective heterogeneous remotely piloted aircraft swarm concepts for ISR missions.

Summary

A vision for a new space system acquisition strategy was summarized in [**3**] that presents disaggregation as an approach "to implement smaller, less-complex satellites and distributed capabilities" that encourages "the lower-cost medium-launch market and allows disaggregation of mission capabilities, which supports mixed constellation of small distributed capabilities complemented by more robust systems" The research presented identified a methodology that enables the optimization of disaggregated space systems and indicates that disaggregated space systems are likely less costly across the system lifecycle with reduced overall risk due to catastrophic system failures. This result has significant implications related to the reduction of space system life cycle costs, increased space system resiliency, reduced development and production timelines, improved space systems engineering education and knowledge base, a stabilized industrial base, and improved resource allocation capability. The disaggregation strategy and the DISCO methodology are promising areas for future research and have the potential to be a positive disruptive force in the space systems enterprise.

Appendix A – Expanded Space Systems Optimization Literature Review

Research into disaggregated space system optimization is currently in its infancy. On-going research into disaggregated space system conceptual architectures is split-up between two active research areas. Disaggregation of existing space system architectures is the first area of active associated research. General optimization of space systems designs is the second area of active research. In general disaggregation research has been subjective and at a top level and space system design optimization has been focused on subsystems, orbits, or subsections of the disaggregated space system conceptual design problem.

Current research into the active disaggregation of space systems is largely limited to qualitative assessments of possible benefits and a few pathfinder applications of disaggregation strategies. Some initial qualitative research into the impacts of disaggregation has been completed by the US Air Force Space Command (AFSPC) and its acquisition organization the Space and Missiles Systems Center (SMC). AFSPC has completed a white paper summarizing the expected qualitative impacts of the disaggregation strategy [**36**]. AFSPC is also completing a series of top level studies evaluating the disaggregation of space systems associated with the current primary AFSPC mission areas. SMC executives have also completed a qualitative assessment of benefits associated with disaggregating the current primary SMC mission areas (Pawlikowski, Loverro, & Cristler, 2012). There are also a few examples of disaggregated space system programs associated with the various disaggregation strategies. The current analysis regarding disaggregation is limited by the qualitative

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nature of the research. Assertions are made to the benefits and potential drawbacks

without numeric or empirical verification.

There are significantly more examples of space system optimization. Current research

related to space system optimization can be split into applications based upon the system

focus and the dynamic state of the systems. The primary limitation of space system

optimization research to date is the inability to assess multi-system (heterogeneous)

multi-orbit (spatially-distributed) problems that arise from practical disaggregated space-

system architecture problems.

Previous Space system optimization research

Cyrus D. Jilla provided a thorough literature review of Multi-disciplinary Design

Optimization (MDO) techniques applied to the space system optimization in his Ph.D.

thesis titled <u>A Multiobjective, Multidisciplinary Design Optimization Methodology for</u>

<u>the Conceptual Design of Distributed Satellite Systems</u>.   According to Jilla "the first

formal applications of optimization within the aerospace field occurred within specific

specialties". The two-impulse Hohmann transfer ellipse minimizing energy transfer and

Walker-Delta constellations minimizing N satellite continuous global coverage are two

well-known orbital dynamics engineering specialty optimization examples. Additionally,

Jilla claims that much of the previous optimization in the aerospace field entails

"optimizing individual components (e.g. orbit) or subsystems… and then integrating

these components and subsystems together" [**55**]. This approach often does not

necessarily produce globally optimum or near optimum systems of systems. In

conducting a detailed literature review on disaggregated space system design

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optimization I have concluded that there has been minimal change in the research

environment associated with disaggregated space system conceptual design optimization.

In addition I have identified that the multi-system (heterogeneous) spatially distributed

(unknown orbit) is lacking academic research. This optimization design space is also the

most applicable to real-world disaggregation problems.   This literature review analysis

is summarized in Figure 29 and the justification for this figure is detailed in the following

prospectus sub-sections.   The intent of the following paragraphs is to justify the claim

that research conducted into the optimization of heterogeneous space systems in

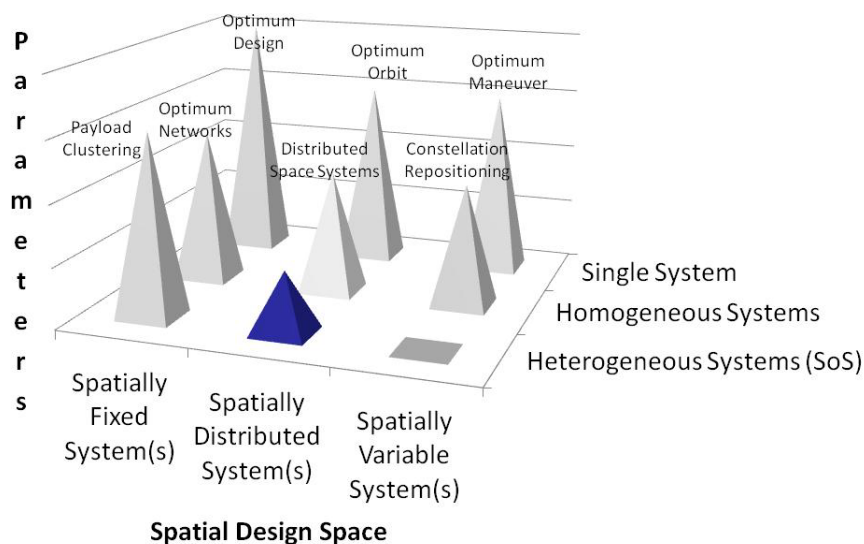unknown locations is worthwhile AFIT doctoral research.

Figure 29 - Summary of academic research associated with system design optimization

Single System/Specified Location

Todd Mosher was one of the pioneers in space systems optimization for a single

satellite in an assumed orbit. His 1998 IEEE aerospace conference paper titled

Spacecraft Design Using a Genetic Algorithm Approach outlined a method for modeling

a spacecraft as a mixed integer problem formulated to minimize cost under performance constraints. Using genetic algorithm optimization methods he demonstrated the utility of the approach on the conceptual design of the Near Earth Asteroid Rendezvous (NEAR). He expanded his method and applied it to the Mars Global Surveyor and an original Eagle-eye commercial lunar mission in his Ph.D. dissertation entitled Improving Spacecraft Design Using a Multidisciplinary Optimization Methodology. Mosher continued on to develop tools for the optimization of space-system component selection. Numerous articles followed Mosher's work on the optimization of spacecraft systems or components in a pre-defined or known orbit. A significant amount of research in this area use genetic algorithms or other metaheuristics to assess combinatorial non-linear optimization problems. Rania Hassan et al. compare the performance of a Particle Swarm Optimization (PSO) algorithm and a Genetic Algorithm (GA) applied to a geostationary communication satellite design problem in their article titled A Comparison of Particle Swarm Optimization and the Genetic Algorithm [67]. Sherman used a genetic algorithm to optimize the design of the phased array antenna shape and antenna patterns as discussed in article titled Phased array shaped multi-beam optimization for LEO satellite constellations [68]. These are just a few examples of the multitude of articles on space system or space system component optimization for a single system in a specified location. Fasano and Pinter's book titled Modeling and optimization in space engineering also contain examples for global optimization of sensor placement and subsystem placement for single satellite designs [69]. This research is fundamental to the DS3O methodology as it demonstrates space system parameters can be optimized for cost and performance effectiveness using metaheuristic optimization techniques.

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Homogeneous Systems/Specified System Locations

Generally, there was significantly less academic research in the arena of homogeneous space systems with specified system location than I first assessed. A significant amount of research that attempted to optimize parameters associated with constellations of homogeneous satellites also addressed the parameterization of a minimal subset of orbital parameter such as circular orbit altitude. A few academic research articles were identified that optimized the payload configurations of geosynchronous communication satellites in assumed geostationary locations. . For example, Rita Rinaldo and Riccardo De Gaudenzi addressed the optimization of forward and return links for multi-beam satellite broadband systems [**70**]. Additionally McCormick et. al. investigated the optimization of a fractionated NPOESS satellite constellation in their AIAA space conference paper titled Analyzing Fractionated Satellite Architectures Using RAFTIMATE [**71**]. This paper used a value analysis approach to optimize design and test whether a fractionated National Polar Orbiting Earth Sensing System (NPOESS) constellation provided more robust value than a non-fractionated design. There was significantly more research in the optimization of terrestrial communication systems vs. space systems. This is likely due to the fixed location of communication system vs. the fundamentally dynamic nature of space systems. The research in this context has minimal impact on the proposed research as the DISCO methodology fundamentally attempts to address the association of space system performance and the orbital location and the corresponding impact on space system cost.

Heterogeneous Systems of Systems/Specified Locations

There is some significant research in the context of heterogeneous space systems in specified locations. Mark G. Matossian is often cited as a pioneer in heterogeneous space system optimization. His article titled <u>Earth Observing System Constellation Design Optimization through Mixed Integer Programming</u> was one of the first space system optimization efforts that transitioned from assuming identical spacecraft and optimizing coverage to optimizing spacecraft configurations with varied payloads. Matossian used a branch and bound algorithm with linear equations representing the combination of pre-existing payloads that are clustered on spacecraft and launch vehicles for optimal cost vs weighted mean science performance. An example of the output of his optimization method and corresponding sensitivity analysis is shown in Figure 30. His optimization approach was used to make the claim that the on-going rebaseline of EOS instruments was non-optimal. This approach varies significantly from the DISCO methodology in its use of pre-defined sensors, linear assumptions, subjective instrument performance matrices, and the use of pre-defined orbits [**37**].

The Efficient Frontier
Sensitivity of Instrument Candidate Pool

Instrument Availability

◇ Original EOS Instruments
○ Current EOS Instruments
△ Force AM-1 + Current Instr.

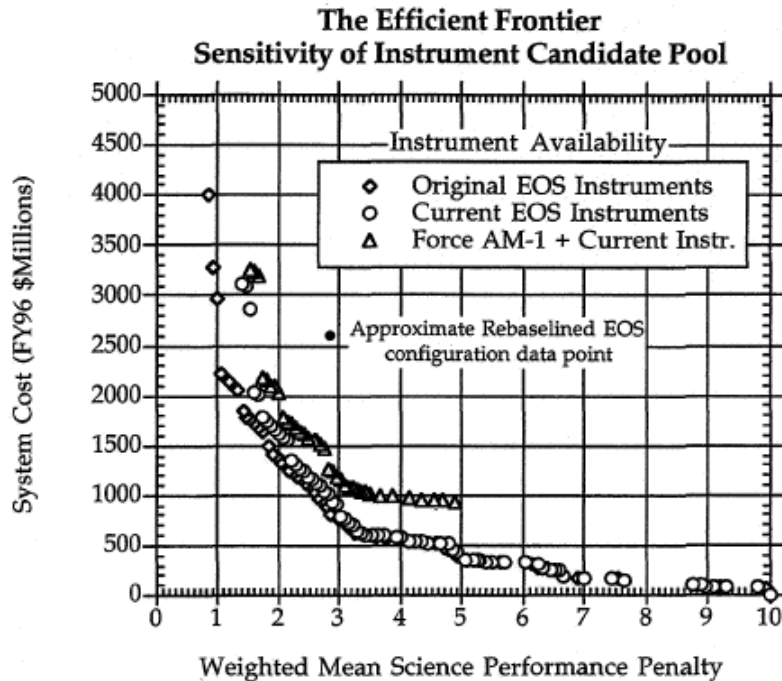● Approximate Rebaselined EOS configuration data point

Figure 6.1 Without a systems-oriented optimization tool, it is difficult to know which instruments to eliminate during the original selection process or during downsizing exercises. While the model does not capture all the many factors taken into consideration in instrument selection, the closest analog to the "Rebaseling" re-design process would consider only the surviving EOS instruments as candidates and force the use of the AM-1 spacecraft in the final configuration. NASA's actual Rebaselined EOS configuration is included above, and does not compare favorably with the efficient frontier graph for the analog

Figure 30 – Example cost vs. weighted mean science return output [**37**]

Daniel Selva, Bruce G. Cameron, and Edward F. Crawley have recently extended Matossian's approach to optimization of the EOS constellation using population-based heuristics with expert opinion derived rules to optimize clusters of previously existing EOS sensors on notional spacecraft and launch vehicles. In their Earth Sciences Decadal survey report titled Rule-Based System Architecting of Earth Observing Systems: The Earth Science Decadal Survey they applied genetic algorithms to the packaging of EOS sensors without the linear assumption used be Matossian and with expanded qualitative rules based upon expert assessment of scientific payoff of varying payloads [**72**]. In

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Selva and Crawley's paper <u>Integrated Assessment of Packaging Architectures in Earth Observing Programs</u> they include qualitative analysis of lifecycle cost, and programmatic risk based upon fuzzy rules derived from qualitative analysis. Selva also recently performed a preliminary assessment of performance and cost of a cubesat component of the earth science decadal survey [**73**]. The Selva et al. research differs from the proposed DISCO methodology because it clusters pre-existing sensors vs. parameterization of sensors and orbits. The work also assumes a few orbital locations based upon the current orbits of existing sensors rather than the global optimization of orbital parameter. Although this work does not address the optimization of system parameters and location (orbital) parameters it does provide valuable background on effective formulations for heterogeneous satellites with mixed sensors. Additionally, this research also provides some indications of effective ways to address lifecycle cost risk and programmatic risk [**72**].

Overall, there is a significantly smaller amount of previous academic research into optimization of heterogeneous space systems than optimization of satellite or satellite component design.

<p align="center">**Single System/Unknown Location**</p>

A significantly larger body of research is applied to the optimization of orbital parameters based upon assumed satellite systems. Kim et al. use a genetic algorithm to optimize the local coverage problem of imagery satellites in their paper titled <u>A computational approach to reduce the revisit time using a Genetic Algorithm</u> [**74**]. The Fasano et. al text <u>Modeling and optimization in space engineering</u> contains numerous additional research articles analyzing global optimization applied to single spacecraft

<p align="center">154</p>

orbits and transfers. The Fasano et al. text addresses global optimization approaches for optimal trajectory planning, indirect methods form the optimization of spacecraft trajectories, trajectory optimization for launchers and re-entry vehicles, global optimization of interplanetary transfers, and optimization of low energy transfers [**69**]. AFIT has also contributed significant research to the single system unknown location optimization problem. One notable example is the AFIT thesis titled THE UTILITY AND LOGISTICS IMPACT OF SMALL-SATELLITE CONSTELLATIONS IN MATCHED INCLINATION ORBITS. Emery et al. researched the optimal placement (RAAN placement only) of a tactical spacecraft and ground terminal to optimize the number of available imagery download opportunities [**75**]. This could be categorized as heterogeneous system as the optimization included a satellite and ground terminal however the location of the ground terminal was selected at identified locations and was not part of the optimization routine. This report was extended to homogeneous satellite constellation of up to five satellites but the number of satellites was likewise not included in the optimization routine.

Homogeneous Systems/Unknown System Locations

Significantly more research has been conducted in the arena of homogeneous systems with unknown system location than previously assessed. Irene A. Budianto and John R. Olds used a genetic algorithm approach to optimize alternative Space Based Infrared System (SBIRS) low satellite constellations in their paper titled A Collaborative Optimization Approach to Design and Deployment of a Space Based Infrared System Constellation. The investigated varying satellite altitude, inclination, and sensor view angles to minimize system cost then assigned an optimum launch vehicle to the chosen

constellation as a sub-problem [**76**]. Sorenson et al. analyzed the optimal orbital placement of an ocean temperature small satellite constellation in their article titled Mission Design and Operations of a Constellation of Small Satellites [**77**].

There was also a significant amount of research applying multi-objective optimization to determine effective orbits for homogeneous satellite constellations. William J. Mason conducted fundamental research in this area that is summarized in his doctoral dissertation and corresponding articles titled Optimal Earth Orbiting Satellite Constellations via a Pareto Genetic Algorithm. In this research Mason investigated the optimization of inclined geosynchronous satellite orbits [**78**]. Matthew P. Ferringer extended Mason's research to other orbit types and investigated parallel processing efficiencies. Ferringer, and David Spencer analyzed the optimization of earth observing system ground sample distances vs. mean revisit time for varied orbital parameter in their article titled Satellite Constellation Design Tradeoffs Using Multiple-Objective Evolutionary Computation [**79**]. Ferringer, Clifton, and Thompson then analyzed the efficiencies of different parallel processing schemes to constellation orbit optimization in their article titled Efficient and Accurate Evolutionary Multi-Objective Optimization Paradigms for Satellite Constellation Design [**80**].

The most comprehensive research into the optimization of homogeneous satellite constellations and unknown orbital locations was Cyrus D. Jilla's dissertation titled A Multi-objective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems. Jilla analyzed a small set of Walker orbit constellation variations with discrete payload parameters for a constellation design of radar, planet finding, and broadband communication satellites [**55**].

Overall there was a significantly larger effort into the optimization of homogeneous space systems with unknown system locations than previously assessed. The research landscape figure was adjusted accordingly to show a subjectively larger body of research knowledge in this area. The research in this area differs from the DISCO methodology because all of the research assumes homogeneous satellite constellations.

Heterogeneous Systems/Unknown System Locations

I was unable to identify any previous research where optimization techniques are used to identify heterogeneous satellite parameters and system location (orbit) parameters.

Single System/Variable System Location

The optimization research in the area of single systems and variable systems is significant but largely is focused on the minimization of fuel vs. the DISCO methodology minimizing cost against performance constraints. There is a significant amount of research into solving orbit optimal control problems. Some examples include Chistof Buskens and Helmut Maurer <u>SQP-methods for solving optimal control problems with control and state constraints: adjoint variables, sensitivity analysis and real-time control</u>. Bradley J. Wall and Bruce A. Conway's article titled <u>Genetic algorithms applied to the solution of hybrid optimal control problems in astrodynamics</u>. The multitude of minimum fuel optimization problems have little correlation to the DISCO methodology. A few research articles have attempted to optimize the coverage performance aspect of the DISCO methodology in a variable system location.   One good example of this approach is Thomas C. Co, Costantinos Zagaris, and Jonathan T. Black's article titled <u>Responsive Satellites Through Ground Track Manipulation Using Existing Technology</u>

[**81**]. In this article the authors use optimal control methods to investigate the possibility of increasing operational coverage responsiveness by optimizing orbit maneuvers based upon available time and varied propulsion types. Overall, the research identified in this area was consistent with the original subjective assessment shown in the research landscape summary figure. However, significantly more research could be performed in this area regarding the increase in overall system capability and the potential reduction in cost provided by maneuverable space systems.

Homogeneous Systems/Variable System Location

Some research has been conducted into the optimization of satellite orbit reconfiguration to meet multiple performance objectives while minimizing fuel costs. A good example of this research is Matthew P. Ferringer, David B Spencer, and Patrick Reed's article titled Many-objective reconfiguration of Operational Satellite Constellations with the Large-Cluster Epsilon Non-dominated Sorting Genetic Algorithm-II [**82**] . In this article the authors describe a method to optimize maneuvers given the notional loss of a GPS satellite. The authors were able to identify solutions that balanced coverage, signal strength, propellant usage, and time of flight using a multi-objective genetic algorithm technique. They also analyzed the precursors to this research in their conference paper titled Pareto Hypervolumes for the Reconfiguration of Satellite Constellations [**83**]. Overall, an initial assessment of the homogeneous system/variable location system architecture was originally unknown. It appears that there is a significant amount of research in this area though less than the single system/variable location design space. This existing research also varies significantly from the DISCO

methodology because it does not address overall system cost or performance and typically focuses on the optimization of orbital transfer maneuvers.

Heterogeneous Systems/Variable System Location

I was unable to identify any academic publication regarding the optimization of heterogeneous space systems with variable system locations.

Appendix B – Additional Methodology Development

Additional methods were developed during this research related to reference architecture development and architecture/model concordance. The following sections of this appendix provide an example of the methods used for developing the WSF reference architecture and establishing concordance between this architecture and the DISCO models. These methods were not fully described in the research manuscripts. Consequently, a description of these methods is included in this appendix.

A reference space based weather domain architecture description was developed for WSF. A summary of this mission domain architecture is presented in Figure 31 showing the system, interfacing systems, and the relevant environment.
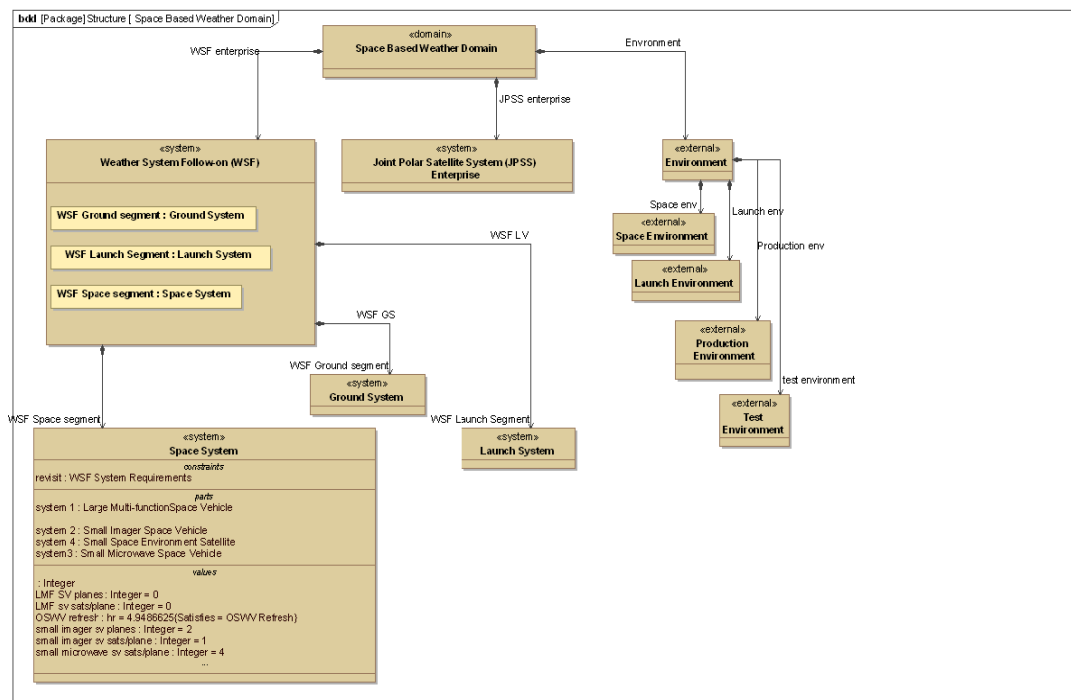
Figure 31. Reference WSF mission domain architecture

A reference system architecture description was then developed for WSF. An overview of this reference system architecture is displayed in Figure 32 displaying the logical architecture with the potential system types and their component composition.
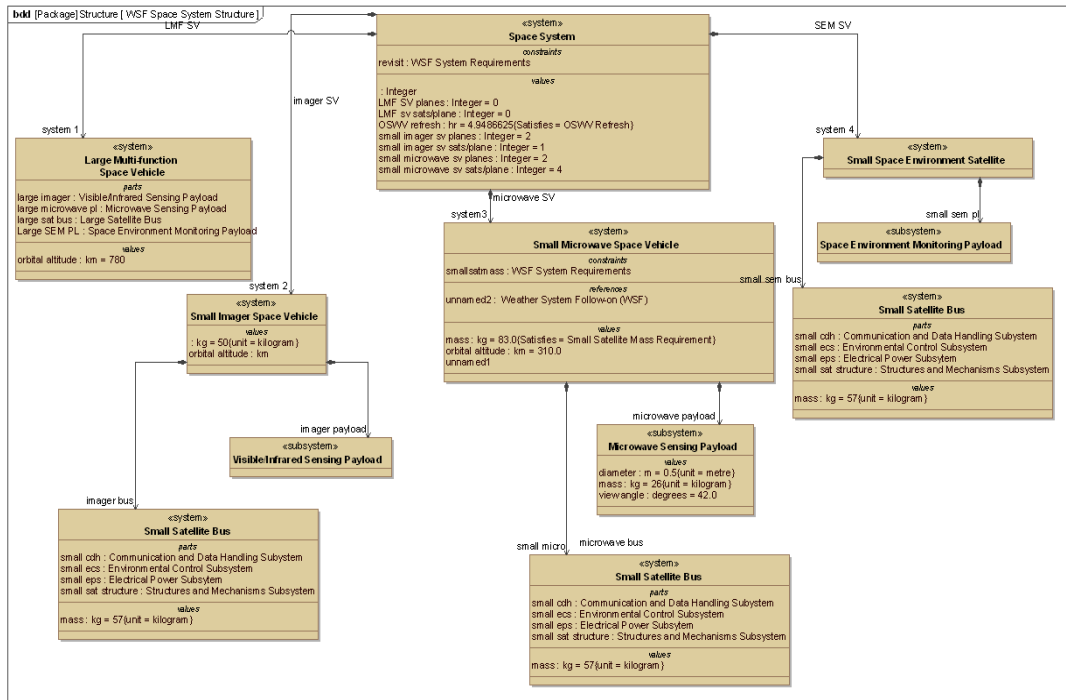

Figure 32. WSF reference system architeture description

Applicable system requirements were then built in requirements diagrams associated with the system component of interest. These system requirements are stereotyped as property based requirements allowing a linkage between the textual requirements and a numerically calculated requirement value. The property based requirements are then copied into a block diagram linking the calculated value and the property based requirement. This linkage is established as a satisfy requirement relationship as shown in Figure 33
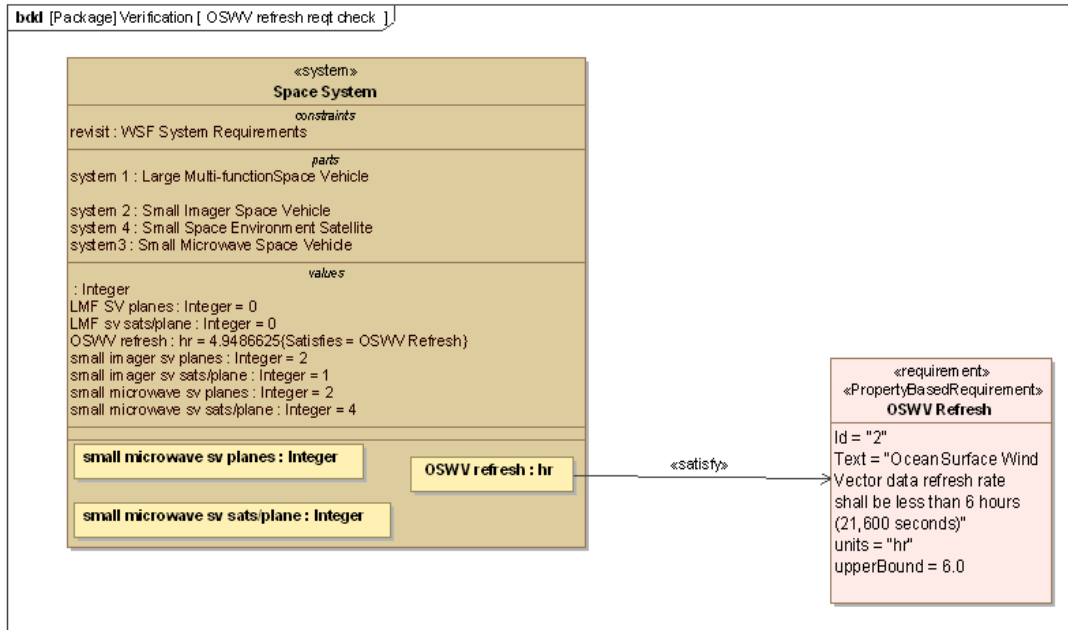
Figure 33. Example satisfy requirement relationship

The software performance and dynamic model functions are imported into ModelCenter

® as data analysis model components. The input and output variables used by the

architecture model are defined and exposed as external variables. A SysML constraint

block is then created using the MBSE analyzer plug-in and links between the system

architecture reference model variables and performance/dynamics model variables are

created as shown if Figure 34.   The linkage between variables is a key step in the

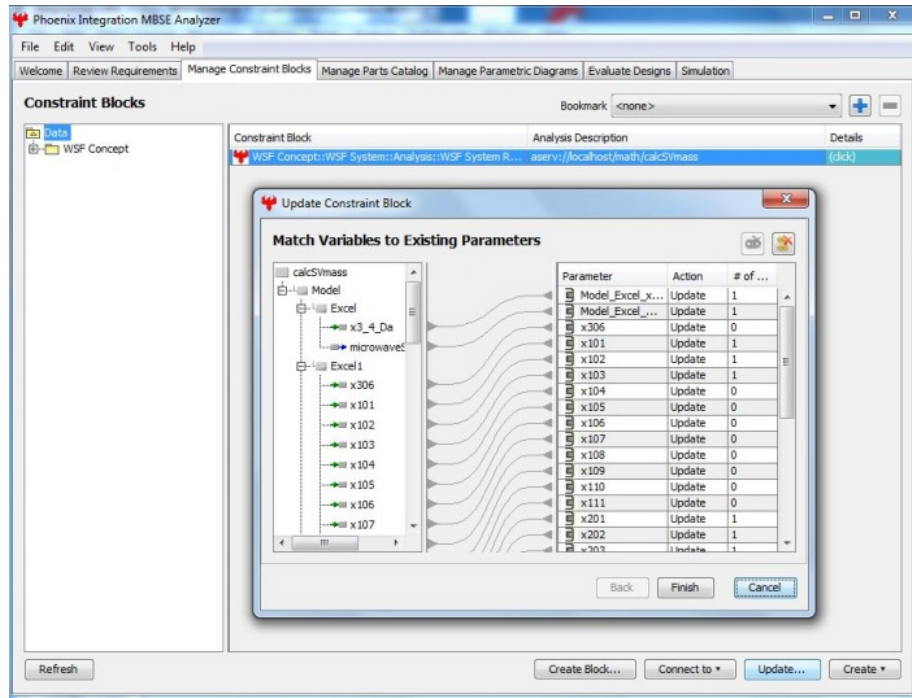concordance process between the integrated models.

Figure 34. Overview of constraint block creation

A Parametric diagram is then created for the system component associated with the

requirement to be verified. For example the OSWV revisit is a space system level

requirement and therefore a parametric diagram is created for the space system block

shown in Figure 32. Binding parameters are then established linking the system value

components with the appropriate input and output parameters as shown in Figure 35.
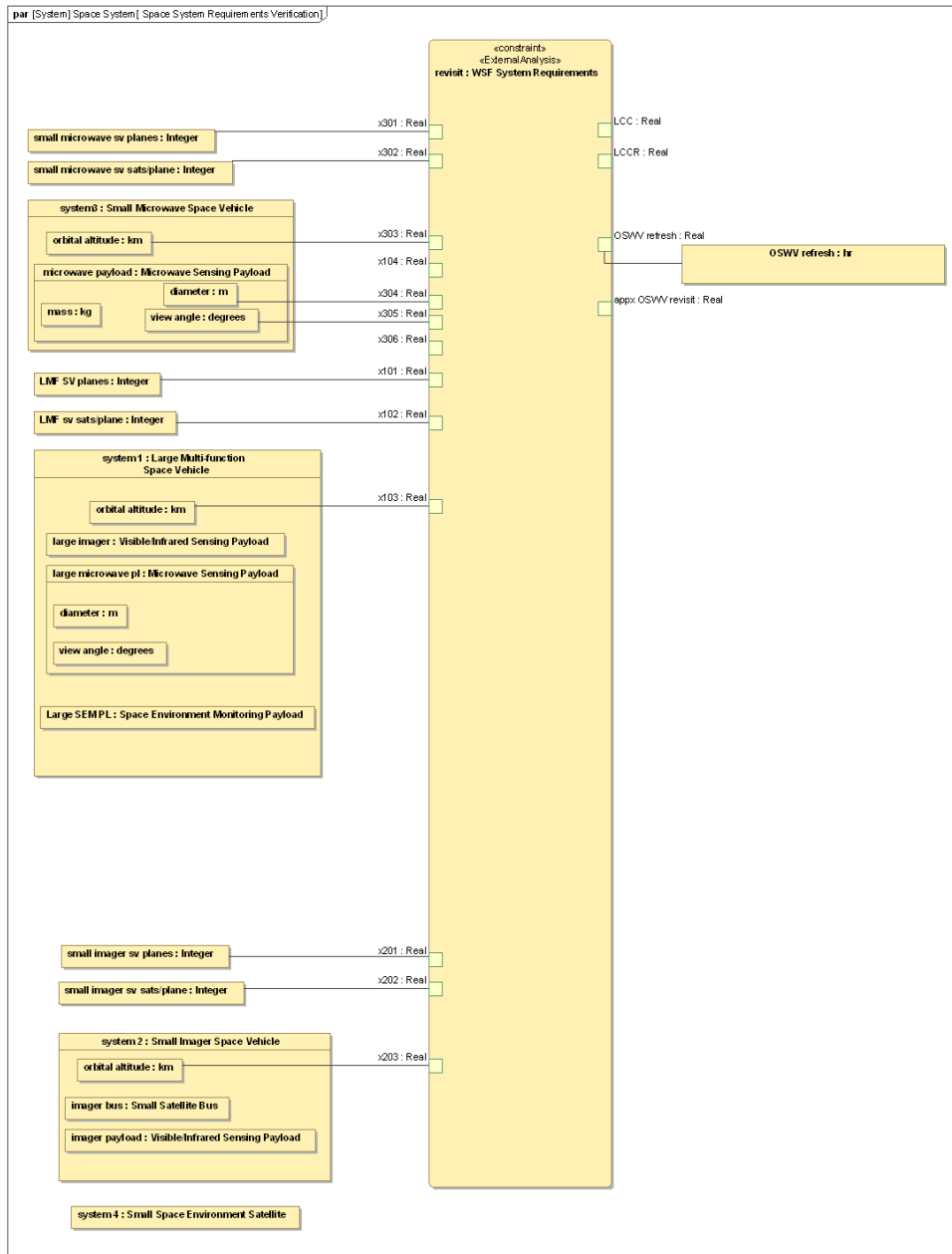
Figure 35. OSWV calculation parametric diagram

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The model can now be evaluated based upon the imported default values from the optimization model results. The model is evaluated using the evaluate design functionality built into the MBSE Analyzer® plug-in. Design variables can be adjusted and the corresponding simulation will re-execute the model components as demonstrated in displayed in Figure 36. After the model is executed the resulting system parameters can be saved as the architecture model default values or the updated architecture model can be saved as a design instantiation. This overall process enables the automated update and concordance evaluation for iterative optimization model results. Trades can then be made to finalize the concept design chosen and the selected preferred architecture is documented in the system model. This system architecture model then forms the basis of the system architectural description that will be refined through the system life cycle.
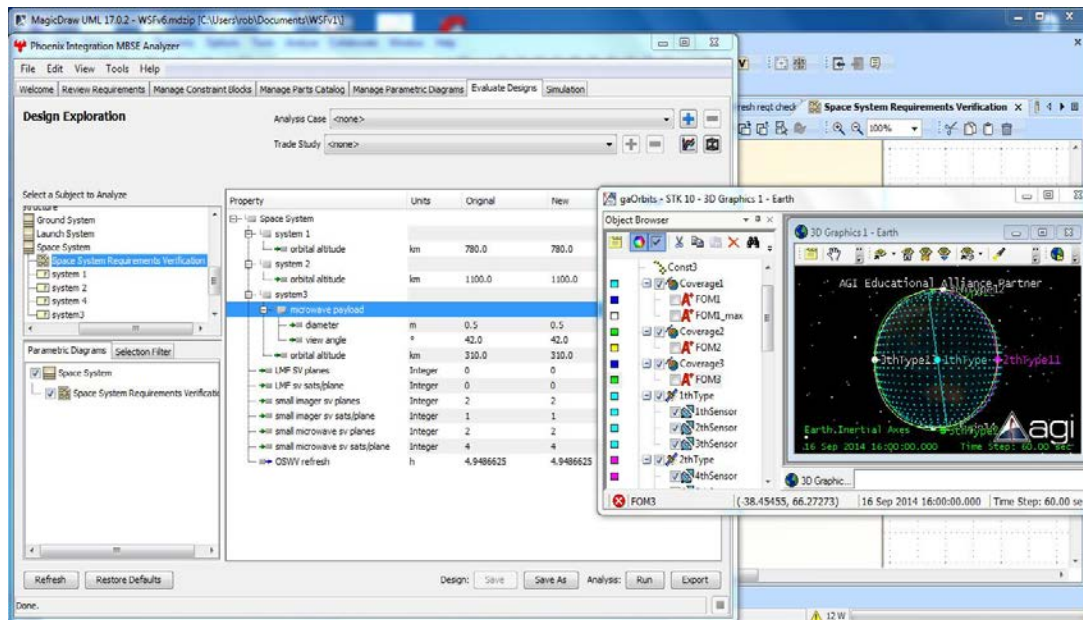

Figure 36. Executable architecture model evaluation.

Bibliography

[1] James R Wertz, David F Everett, and Jeffery J Puschell, *Space Mission Engineering: The New SMAD*. Hawthorn, CA: Microcosm Press, 2011.

[2] J.G. Walker, "Some circular orbit patterns providing continuous whole earth coverage," *Journal of the British Interplanetary Society*, no. 24, pp. 369-384, 1971.

[3] Ellen Pawlikowski, Doug Loverro, and Tom Cristler, "Space: Disruptive Challenges, New Opportunities and New Strategies," *Strategic Studies Quarterly 6, no. 1*, pp. 27-54, 2012.

[4] Christina T. Chaplain et al., "Space Acquisitions: DOD Faces Challenges in Fully Realizing Benefits of Satellite Acquisition Improvements," Washington DC, 2012.

[5] J. J. Simpson and C. H. Dagli, "System of systems architecture generation and evaluation using evolutionary algorithms," in *Systems Conference, 2008 2nd Annual IEEE* , Montreal, 2008.

[6] Air Force Space Command, "Resiliency and Disaggregated Space Architectures - White Paper," 2013. [Online]. www.dtic.mil

[7] Warren Ferster. (2014, Sep) www.spacenews.com. [Online]. http://www.spacenews.com/

[8] Juan F. Lam, Paul La Tour, and Jim Kim, "Architecting Disaggregated Space Weather Solutions using Nanosatellites," in *AIAA SPACE 2013 Conference and Exposition*, San Diego, 2013.

[9] Steven Cornford et al., "Evaluating a Fractionated Spacecraft system: A business case tool for DARPA's F6 program.," in *Aerospace Conference*, Big Sky, 2012, pp. 1-20.

[10] R Thompson, J Colombi, J Black, and B Ayres, "Disaggregated Defense Weather System Follow-on (WSF) Conceptual Architecture Optimization," in *Space*, San Diego, 2014.

[11] INCOSE. (2007, June) INCOSE. [Online]. http://www.incose.org/

[12] INCOSE. (2013, March) INCOSE. [Online]. http://www.incose.org/

[13] INCOSE, *Systems Engineering Handbook: A Guide for System Life Cycle Processes and Activities"*. San Diego: INCOSE, 2011.

[14] R.L. Keeney and H. Raiffa, *Decisions with multiple objectives–preferences and value tradeoffs*. Cambridge & New York: Cambridge University Press, 1993.

[15] Todd Mosher, "Conceptual spacecraft design using a genetic algorithm trade selection process," *Journal of Aircraft*, pp. 200-208, 1999.

[16] Alessandro Aliakbargolkar, Edward F Crawley, Anthony C Wicht, Jonathan A Battat, and Emily D Calandrelli, "Systems Architecting Methodology for Space Transportation Infrastructure," *Journal of Spacecraft and Rockets*, vol. 50, no. 3, pp. 579-590, 2013.

[17] Mark G Matossian, "Earth Observing System constellation design optimization through mixed integer programming.," *Space Technology*, pp. 233-243, 1996.

[18] Cyrus D. Jilla and David W. Miller, "Multi-objective, multidisciplinary design optimization methodology for distributed satellite systems," *Journal of Spacecraft and Rockets*, vol. 41, no. 1, pp. 39-50, 2004.

[19] Graeme B. Shaw, David W. Miller, and Daniel E. Hastings, "Development of the quantitative generalized information network analysis methodology for satellite systems," *Journal of Spacecraft and Rockets*, vol. 38, no. 2, pp. 257-269, 2001.

[20] Daniel Selva, Bruce Cameron, and Edward Crawley, "Rule-based System Architecting of Earth Observing Systems: The Earth Science Decadal Survey," *Journal of Spacecraft and Rockets*, pp. 1-17, 2014.

[21] Sanford Friedenthal, Alan Moore, and Rick Steiner, *A practical guide to SysML: the systems modeling language*.: Access Online via Elsevier, 2011.

[22] J. Arora, Introduction to optimum design, 2004.

[23] William A Crossley and Edwin A Williams, "Simulated Annealing and Gentic Algorithm Approaches for Discontinuous Coverage Satellite Constellation Design," *Engineering Optimization*, pp. 37-47, 2007.

[24] A. Aliakbargolkar and E. F. Crawley, "Architecting methodology for spatially and temporally distributed resource extraction systems," *Systems Engineering*, vol. 16, no. 3, pp. 277–286, 2012.

[25] Carlton R Pennypacker and Marek K Jakubowski, "FUEGO-Fire Urgency Estimator in Geosynchronous Orbit - A Propese Early-Warning Fire Detection System," *Remote Sensing*, pp. 5174-5192, 2013.

[26] D. Escorial, I. F. Tourne, and F. J. Reina, "Fuego: A dedicated constllation of small satellites to detect and monitor forest fires," *Acta Astronautica*, pp. 765-775, 2003.

[27] Christopher L Delp. (2008) JPL. [Online]. http://mbse.gfse.de

[28] W. J. Larson and J. R. Wertz, *Space mission analysis and design*. Torrance, CA: Microcosm, Inc., 2006.

[29] Robert E Thompson, John Colombi, Jonathan Black, and Brad Ayres, "Computer Aided Design of Disaggregate Systems," in *IEEE Aerospace*, Big Sky, MT, 2014.

[30] Azad M Madni, "Generating Novel Options during Systems Architecting: Psychological Principles, Systems thinking, and Computer Based Aiding," *Systems Engineering*, vol. 17, no. 1, pp. 1-9, 2013.

[31] NOAA. (2014, April) About NESDIS. [Online]. http://www.nesdis.noaa.gov/about_nesdis.html

[32] US Air Force. [Online]. http://www.losangeles.af.mil/library/factsheets/factsheet.asp?id=4644

[33] Michael Bennett, "Options for Modernizing Military Weather Satellites," Washington D.C., 2012.

[34] Mike Gruss. (2014, March) Disaggregation Gets Traction in 2015 Pentagon Budget Request. [Online]. Disaggregation Gets Traction in 2015 Pentagon Budget Request

[35] John P. Baldonado. (2014, February) [Online]. http://www.goes-r.gov/downloads/AMS/2014/pres/02-04/03-Larrimore.pdf

[36] Air Force Space Command, "Resiliency and Disaggregated Space Architectures - White Paper," 2013.

[37] Mark G Matossian, "Earth Observing System constellation design optimization through mixed integer programming.," in *The Sixth Alumni Conference of the International Space University* , 1997, pp. 1-12.

[38] Cyrus D Jilla, "A Multiobjective, Multidisciplinary Design Optimization Methodology for the Conceptual Design of Distributed Satellite Systems - Dissertation," Massachussets Institution of Technology, Cambridge, MA, Dissertation 2002.

[39] Robert E Thompson, John M Colombi, Jonathan Black, and Bradley J. Ayres, "Model-Based Conceptual Design of Disaggregated Space System Architectures," *Journal of Systems Engineering*, unpublished.

[40] Dennis M Buede, *The Engineering Design of Systems*. New York: John Wiley and Sons Inc, 2000.

[41] Sanford Friedenthal, Alan Moore, and Rick Steiner, *A Pracitical Guide to SysML.* Waltham, MA: Morgan Kaufmann, A practical guide to SysML: the systems modeling language.

[42] Robert E Thompson, John Colombi, and Jonathan Black, "Computer-Aided Architecting of Disaggregated Space Systems," in *IEEE Aerospace Conference*, Big Sky, MT, 2014.

[43] C. Schueler et al., "VIIRS sensor performance," in *INTERNATIONAL GEOSCIENCE AND REMOTE SENSING SYMPOSIUM*, 2003.

[44] Northrop Grumman, "Algorithm and Data User Manual for the Special Sensor

Microwave Imager/Sounder," Azusa, CA, 2002.

[45] U.S. Department of Defense, "National Polar-orbiting Operational Environmental Satellite System Integrated Operational Requirements Document-II," Washington D.C., 2002.

[46] Brigitte LeBlon, *Applications in Remote Sensing volume 4*. New Brunswick, Canada: University of New Brunswick, 2006.

[47] Jet Propulsion Laboratory. QuikSCAT. [Online]. http://winds.jpl.nasa.gov/missions/quikscat/

[48] DLR. BIRD - The first satellite for spotting forest fires. [Online]. http://www.dlr.de/rd/en/desktopdefault.aspx/tabid-2440/3586_read-5329/

[49] Fawwaz Ulaby, *Microwave remote sensing fundamentals and radiometry*. Reading Massachusetts: Addison-Wesley, 1981.

[50] Air Force Space Command, "Resiliency and Disaggregated Architectures," Colorado Springs, CO, 2013.

[51] Robert E Thompson, John M Colombi, and Jonathan D Black, "Computer-Aided Architecting of Disaggregated Space Systems," in *IEEE Aerospace Conference*, Big Sky, MT, 2014.

[52] Robert E Thompson, John M Colombi, and Jonathan D Black, "Model-Based Conceptual Design of Disaggregated Space System Architectures," *INCOSE Journal of Systems Engineering*, p. In review, 2014.

[53] Robert E Thompson, John M Colombi, Jonathan D Black, and Bradley Ayres, "Disaggregated Defense Weather System Follow-on (WSF) Conceptual Architecture Optimization," in *AIAA Space*, San Diego, 2014.

[54] Robert E Thompson, John M Colombi, Jonathan D Black, and Bradley Ayres, "Model-Based Conceptual Design Optimization Methods: Disaggregated Weather System Follow-On," *AIAA Journal of Spacecraft and Rockets*, p. accepted for publication, 2015.

[55] C. D. Jilla, "Application of Multidisciplinary Design Optimization Techniques to Distributed Satellite Systems," *Journal of Spacecraft & Rockets*, vol. 37, no. 4, pp. 481-490, July 2000.

[56] Joseph H Saleh, Daniel E Hasting, and Dava J Newman, "Spacecraft Design Lifetime," *Journal of Spacecraft and Rockets*, vol. 39, no. 2, pp. 244-257, 2002.

[57] Jean-Francois Castet, "Satellite reliability: statistical data analysis and modeling," *Journal of Spacecraft and Rockets*, vol. 46, no. 5, pp. 1065-1076, 2009.

[58] Gregory F Dubos, Jean-Francois Castet, and Joseph H Saleh, "Statistical reliability analysis of satellites by mass category: Does spacecraft size matter," *Acta Astronautica*, vol. 67, no. 5, pp. 584-595, 2010.

[59] I-Shih Chang, "Space Launch Vehicle Reliability," *Crosslink*, vol. 2, no. i, 2001.

[60] Seth D Guikema and Elisabeth M Pate-Cornell, "Bayesian Analysis of Launch Vehicle Success Rates," *Journal of Spacecraft and Rockets*, vol. 41, no. 1, pp. 93-102, 2004.

[61] Benjamin S Blanchard and Wolter J Fabrycky, *Systems Engineering and Analysis*. Upper Saddle River: Prentice Hall, 2006.

[62] Rania Hassan and William Crossley, "Spacecraft reliability-based design optimization under uncertainty including discrete variables.," *Journal of Spacecraft and Rockets*, vol. 45, no. 2, pp. 394-405, 2008.

[63] Steven Engelen, Eberhard Gill, and Chris Verhoeven, "On the reliability, availability, and throughput of satellite swarms.," *Aerospace and Electronic Systems, IEEE*, vol. 50, no. 2, pp. 1027-1037, 2014.

[64] Jasbir Arora,. *Introduction to optimum design*.: Academic Press, 2004.

[65] Robert E Thompson, John M Colombi, Jonathan D Black, and Bradley Ayres, "Disaggregated Conceptual Design Optimization Methods Applied to the Weather System Follow-on (WSF) Enterprise," *AIAA Journal of Spacecraft and Rockets*, pp. In-review, 2014.

[66] Ed Kyle. (2013, Dec) 2013 Space Launch Report. [Online]. http://www.spacelaunchreport.com/log2013.html

[67] Rania Hassan and Oliver De Weck, "A comparison of particle swarm optimization and the genetic algorithm," in *1st AIAA multidisciplinary design optimization specialist conference*, 2005.

[68] K N Sherman, "Phased array shaped multi-beam optimization for LEO satellite communications using a genetic algorithm," in *IEEE International conference on Technology*, 2000, pp. 501-504.

[69] Girogio Fasano and Janos Pinter, *Modeling and Optimization in Space Engineering*. New York: Springer, 2013.

[70] Rita Rinaldo and Riccardo Gaudenzi, "Capacity analysis and system optimization for the forward link of multi-beam satellite broadband systems exploiting adaptive coding and modulation," *International journal of satellite communication and networking*, pp. 401-423, 2004.

[71] D McCormick, B Barret, and M Burnside, "Analyzing Satellite Architectures Using RAFTIMATE," *AIAA*, p. AIAA, 2009.

[72] Daniel Selva, Bruce Cameron, and Edward Crawley, "Rule-based System Architecting of Earth Observing Systems: The Earth Science Decadal Survey," 2011.

[73] Daniel Selva and David Krejci, "Preliminary Assessment of Performance and Cost of a Cubesat Component of the Earth Science Decadal Survey," 2013.

[74] H. D. Kim, O. C. Jung, and H. Bang, "A computational approach to reduce the revisit time using a genetic algorithm," *Control, Automation and Systems*, pp. 184-189, 2007.

[75] John Emery, Elena Oberg, Kelly Robertson, David Sanchez, and David Smuck, "the utility and logistics impact of small-satellite constellations in matched inclination orbits," WPAFB, 2005.

[76] Irene Budianto and John Olds, "A collaborative optimization approach to design and deployment of a space based infrared system constellation," in *Aerospace*

Conference Proceedings, 2000, pp. 385-393.

[77] Trevor Sorenson, "Mission Design and Operations of a Constellation of Small Satellites," in *Responsive space conference*, 2006.

[78] William Mason, "Optimal Earth orbiting satellite constellations via a Pareto genetic algorithm. Diss.," Urbana, 2001.

[79] Mathew Ferringer and David Spencer, "Satellite constellation design tradeoffs using multiple-objective evolutionary computation," *Journal of spacecraft and rockets*, pp. 1404-1411, 2006.

[80] Matthew P. Ferringer, Ronald Clifton, and Timothy Thompson, "Efficient and accurate evolutionary multi-objective optimization paradigms for satellite constellation design," *Journal of Spacecraft and Rockets*, pp. 682-691, 2007.

[81] Thomas Co, Constatinos Zagaris, and Jonathon Black, "Responsive Satellites Through Ground Track Manipulation Using Existing Technology," *Journal of Spacecraft and Rockets*, pp. 206-216, 2013.

[82] M. P. Ferringer, D. B. Spencer, and P Reed, "Many-objective reconfiguration of operational satellite constellations with the large-cluster epsilon non-dominated sorting genetic algorithm-II," *Evolutionary Computation, 2009*, pp. 340-349, 2009.

[83] Matthew Ferringer, David Spencer, Patrick Reed, and Ronald Clifton, "Pareto-hypervolumes for the reconfiguration of satellite constellations," in *Astrodynamics Specialist Conference and Exhibit*, 2008, p. 6611.

REPORT DOCUMENTATION PAGE	*Form Approved* *OMB No. 074-0188*

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1. REPORT DATE *(DD-MM-YYYY)* 18-06-2015	2. REPORT TYPE Doctoral Dissertation	3. DATES COVERED *(From – To)* May 2013 – June 2015
TITLE AND SUBTITLE A Methodology for the Optimization of Disaggregated Space System Conceptual Designs		**5a. CONTRACT NUMBER**
		5b. GRANT NUMBER
		5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Thompson, Robert E., Major, USAF		**5d. PROJECT NUMBER**
		5e. TASK NUMBER
		5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAMES(S) AND ADDRESS(S) Air Force Institute of Technology Graduate School of Engineering and Management (AFIT/EN) 2950 Hobson Way, Building 640 Wright Patterson Air Force Base OH 45433-7765		**8. PERFORMING ORGANIZATION REPORT NUMBER** AFIT-ENV-DS-15-J-062
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES) (Intentionally left blank)		**10. SPONSOR/MONITOR'S ACRONYM(S)**
		11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
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14. ABSTRACT
Optimal design techniques have proven to be an effective systems engineering tool. Using systems architecture as the foundation, this research explores the use of mixed variable optimization models for synthesizing and evaluating disaggregated space system concepts. Model-based conceptual design techniques are used to identify and assess system architectures based upon estimated system cost, performance trades, and cost risk. The Disaggregated Integral System Concept Optimization (DISCO) methodology is introduced, and then applied to representative space-based missions. Several results are obtained that indicate significant cost effectiveness gains from the optimization of multi-orbit and multi-function/multi-orbit disaggregated space systems. The general methodology has broad applicability for model-based conceptual design (MBCD) of many system types, but is particularly useful for dynamic disaggregated space systems.

15. SUBJECT TERMS
Model Based Systems Engineering, Space Systems, Optimization, Disaggregation

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON Dr. John Colombi, AFIT/ENV
a. REPORT	b. ABSTRACT	c. THIS PAGE	UU	185	19b. TELEPHONE NUMBER *(Include area code)* (937) 255-6565, ext 3347 (NOT DSN) (John.Colombi@afit.edu)
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